CLASSIFIED BOARDS: ENDANGERED SPECIES OR HIDING IN PLAIN SIGHT?*

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Abstract

We combine machine learning with manual inspection to determine the classified board status of over 12,500 firms from 1996 to 2020. We find that while the fraction of S&P 1500 firms with a classified board fell from 58% to 30% over this period, it rose from 40% to 53% for non-S&P 1500 firms. Increasing attention to governance and rising index ownership of S&P 1500 firms appear to drive these trend differences. Our results suggest the conventional wisdom that classified boards are becoming an endangered species is inaccurate for most firms. Rather, they are hiding among firms neglected by commercial databases.

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"The debate is becoming increasingly marginal because classified boards are becoming rare and are on their way toward endangered-species status" – Leo E. Strine Jr. (2014) (Former Chief Justice of the Delaware Supreme Court)

1. Introduction

A fundamental question in corporate governance is whether board structure matters (e.g., Adams, Hermalin, and Weisbach, 2010). One of the most studied yet controversial structures is a classified (staggered) board of directors. With this structure, directors are separated into classes serving staggered terms, with only one class standing for reelection each year. While classified boards can be beneficial if they add to board stability and facilitate long-term strategies (Koppes, Ganske, and Haag, 1999; Cremers, Litov, and Sepe, 2017), they can be detrimental if they insulate inefficient managers from the disciplining effect of the market for corporate control (Faleye, 2007; Cohen and Wang, 2013). Although this debate remains unsettled, descriptive evidence suggests that it is becoming a moot point because a large number of firms have already declassified their boards (Ganor, 2008; Bebchuk, Hirst, and Rhee, 2013), leading many legal experts to quip that classified boards "are on their way toward endangered-species status" (Strine, 2014).[1]

We conjecture that the evidence that classified boards are becoming an "endangered species" is incomplete because it is based solely on the trends of the most prominent U.S. firms, namely, those in the S&P 1500 Composite Index, which account for under a fourth of all public firms. Consequently, we know very little about the classified board status for the vast majority of public firms that represent a significant part of the economy. In this paper, we aim to fill this gap by comparing the trends in board classification for S&P and non-S&P 1500 firms, investigating what drives any differences, and examining whether previously documented associations between classified boards and firm outcomes are similar for S&P and non-S&P 1500 firms.

The primary obstacle in studying classified boards for all U.S. public firms is the lack of coverage by commercial databases. For example, the ISS Governance database (formerly known as the RiskMetrics and IRRC databases and hereafter referenced as ISS) has two crucial coverage

[1] Also echoing this claim, Harvard Law School Professor Guhan Subramanian wrote in a *New York Times* op-ed article that "slowly but surely, corporate America is giving up the staggered board" (Subramanian, 2007).

issues. First, the sample is limited to firms in the S&P 1500 and provides only a snapshot at a given point in time. ISS does not collect data for the years before or after a firm is included or excluded from the Index. Second, between 1990 and 2006, ISS collected data every two to three years, rendering the information stale between collection years. We overcome these limitations by combining textual analysis of annual proxy statements and a powerful machine learning technique – Random Forests (RF) Classifier – to predict whether a firm has a classified board in a given year.

RF Classifier is a popular technique (Varian, 2014) that has been widely applied in various science fields but is relatively new to academic research in finance. RF Classifier grows many decision trees, with each tree bootstrapping the number of observations in a training set and selecting a random number of predictors at each decision node to grow the tree to the largest extent possible. Each tree then gives a classification, and the forest chooses the classification with the highest accuracy. We obtain the optimal classification on classified boards using training and testing samples from ISS, resulting in an initial out-of-sample prediction accuracy rate above 97%. Extending the algorithm to all U.S. public firms over the years 1996-2020, we generate a new dataset containing 104,892 firm-year observations, about triple the size of existing databases. We then manually check all instances for both S&P and non-S&P 1500 firms that are potentially inaccurate and distinguish between the year a firm approves to (de)classify its board and the year the (de)classification is fully implemented because many firms phase (out) in classified boards.[2]

We start our analysis by comparing trends in classified boards for S&P and non-S&P 1500 firms. While 58% of S&P 1500 firms had classified boards in 1996, this figure dropped to 30% by the end of 2020, consistent with the belief that "the day is not far off when [classified] boards will be extinct" (Kahan and Rock, 2009). Among S&P 1500 firms, those in the S&P 500 experienced the most significant drop from 60% in the late 1990s to about 13% in 2020. In stark contrast, the fraction of non-S&P 1500 firms with a classified board increased from about 40% in 1996 to 54%

[2] Differences between when board (de)classification is approved by vote and when it is implemented account for the majority of cases in which our predictions differ from ISS. By manually checking and distinguishing between approval and implementation years, our new classified board dataset improves the coverage of *both* S&P and non-S&P 1500 firms. We detail the construction of our dataset in the Internet Appendix, and our code and data are available at https://sites.google.com/utk.edu/matthew-serfling/data.

by 2002 and has remained near this level through 2020. We find similar trend differences in the rate that firms declassify their boards. Before 2003, all firms declassified at roughly the same rate, but after 2003, S&P 1500 firms began to declassify at a rapidly accelerating rate, reaching a peak of over 9% in 2012. Overall, these findings contradict the claim that classified boards are becoming an endangered species, suggesting instead that they are hiding in plain sight among the large group of public firms neglected by commercial databases.

As to what can explain these different trends, we first examine the role of differences in firm characteristics. While S&P and non-S&P 1500 firms are different along several dimensions, these differences do not completely explain the divergent trends. The trends are very similar after controlling for a broad set of characteristics that might affect a firm's likelihood of being in the S&P 1500, such as age, size, and profitability. Including second-order polynomials of the controls and firm fixed effects or using a propensity score matched sample also cannot explain away the trend differences. These results suggest that a firm's inclusion in the S&P 1500, rather than its characteristics that may correlate with its inclusion, affects whether it has a classified board. For example, the fact that trend differences persist after controlling for firm characteristics and fixed effects, and thus where identification comes from changes in S&P 1500 membership, suggests that there is something unique about being in the Index that pressures firms towards declassification. In fact, we find that during the latter half of our sample, the likelihood that a firm declassifies its board after joining the S&P 1500 increases significantly.

Motivated by these findings, we examine whether S&P 1500 membership creates a "spotlight effect" that pressures member firms to declassify their boards. Our findings that the relation between declassification and index inclusion changes over time points towards a structural shift in attitudes towards classified boards. We conjecture that an increase in attention to governance following the accounting scandals in the early 2000s, especially for prominent firms that tend to dominate the news, combined with larger passive index fund ownership, could pressure S&P 1500 firms to declassify (e.g., Bebchuk, Cohen, and Wang, 2013; Appel, Gormley, and Keim, 2016). Beginning in the early 2000s, the number of Wall Street Journal (WSJ) articles mentioning corporate governance and academic papers on classified boards started to increase. At the same time, passive (quasi-indexer) ownership of S&P 1500 firms rose substantially from 27% to over 60%, while it increased from 14% to about 30% for non-S&P 1500 firms. Increases in ownership by the "Big Three" index fund managers (i.e., Blackrock, Vanguard, State Street) were also more pronounced for S&P 1500 firms, rising from 4% in the early 2000s to nearly 25% in 2020, while only increasing from 1% to around 10% for non-S&P 1500 firms.

This large rise in passive ownership is important because these investors cannot simply sell shares if they are displeased with a firm's governance policies. Instead, they are forced to "shine the spotlight" and engage management to advocate for changes (McCahery, Sautner, and Starks, 2016). Pointing toward the effectiveness of index funds' ability to shape governance, starting in 2010, the relation between having a classified board and both quasi-indexer and Big Three ownership becomes negative. Moreover, when we evaluate our regression models' ability to predict trends in classified board usage by S&P 1500 firms, removing any effect of quasi-indexer and Big Three ownership worsens the explanatory power by 20.3% and 9.1%, respectively. Further consistent with a spotlight effect that shifts sentiment against classified boards and increases shareholder involvement, S&P 1500 firms are on average over five times more likely to vote on proposals for declassification. In addition, the fraction of "for" votes on these proposals steadily increases among S&P 1500 firms, while this pattern is less visible for non-S&P 1500 firms.

Lastly, we explore whether trend differences in M&A activity play a role in explaining the trend differences in classified boards between S&P and non-S&P 1500 firms. For instance, if potential acquirers are more likely to target non-S&P 1500 firms in the latter part of our sample, then it could be that these firms are also more likely to have classified boards as an antitakeover provision, resulting in more of these firms maintaining a classified board over time. Inconsistent with this explanation, we do not find material differences in the trends in the fraction of S&P and non-S&P 1500 firms being acquired between 1996 and 2020.

The remainder of our paper investigates whether previously documented associations between classified boards and firm outcomes are similar for S&P and non-S&P 1500 firms. Our goal for this analysis is to confirm whether there are differences in prior findings between S&P and non-S&P 1500 firms, setting aside causal explanations of any differences for future work. First, following Masulis, Wang, and Xie (2007), we examine how classified boards are related to acquisition performance for firms in the ISS sample over the 1990-2003 period, finding that having a classified board is significantly negatively correlated with a bidder's cumulative abnormal return (CAR) around the announcement of a deal. However, this negative association becomes insignificant over the years 1996-2020. Yet, among non-S&P 1500 firms over this period, the relation remains significantly negative, consistent with the authors' interpretation that classified boards are associated with value-destroying "empire building." Next, we revisit the relation between classified boards and earnings management following Zhao and Chen (2008) and find a significantly negative association in the ISS sample over the years 1995-2001 and 1996-2020. This finding is consistent with the authors' view that classified boards enable managers to enjoy the "quiet life." However, this association disappears for non-S&P 1500 firms.

We also revisit the association between classified boards and firm value. Our first "cross-sectional" specification follows Faleye (2007) and focuses on the ISS sample from 1995 to 2002 and includes industry and year fixed effects. Consistent with his "managerial entrenchment" view of classified boards, we also find a negative association between classified boards and Tobin's Q. This result holds over the 1996-2020 period and is especially strong for non-S&P 1500 firms. Conversely, Cremers, Litov, and Sepe (2017) show that the association between classified boards and Tobin's Q becomes significantly positive in "time-series" specifications that include firm fixed effects, consistent with a "bonding" mechanism. While we confirm this result for S&P 1500 firms, the association remains negative but insignificant for non-S&P 1500 firms.

Our paper contributes to the literature in several ways. First, we make a methodological contribution by demonstrating how machine learning can be used to construct comprehensive datasets that offer better representations of sample populations. While machine learning is applied in the finance literature (e.g., Gu, Kelly, and Xiu, 2020; Bianchi, Büchner, and Tamoni, 2021; Erel, Stern, Tan, and Weisbach, 2021; Li, Mai, Shen, and Yan, 2021), its use has been primarily for measuring latent variables (e.g., asset risk premiums, corporate culture) and predicting financial returns and corporate performance. To the best of our knowledge, we are the first to use machine learning to overcome the sampling limitations of a commercial database.[3] We apply this methodology to classified boards, but future research can adopt our approach to other settings.

Second, we extend the literature analyzing how board structures (e.g., size, independence, expertise, diversity) affect firm performance (e.g., Yermack, 1996; Bebchuk and Cohen, 2005; Adams and Ferreira, 2009; Duchin, Matsusaka, and Ozbas, 2010; Field and Mkrtchyan, 2017). Except for classified boards, advances in data availability have expanded prior inferences on board structures to beyond the largest public firms (e.g., Dass et al., 2014; Chen, Chen, Kang, and Peng, 2020; Field, Souther, and Yore, 2020). We contribute to this literature by documenting differences in the use of classified boards between S&P and non-S&P 1500 firms, providing complete and novel evidence on the prevalence of this board structure, both cross-sectionally and over time.

A few studies consider the use of classified boards outside the S&P 1500 by focusing on the takeover defenses of firms going public. This work finds that IPO firms deploy takeover defenses to deter subsequent takeovers and protect key relationship-specific investments and that the benefits of these defenses reverse as they age (Field and Karpoff, 2002; Johnson, Karpoff, and Yi, 2015, 2022). Closest to our study, Field and Lowry (2022) find that IPO firms have mostly increased their use of classified boards over time, especially among firms with high information asymmetry that benefit the most from protection from short-term market pressures. Our work adds to these studies by investigating trend differences in the use of classified boards by *all* public firms, which we show are not driven by IPO firms. In fact, firms that have been public three years or less account for only 12% of our sample, and the trend differences we find are similar if we include firm age fixed effects, use a matched sample that matches exactly on age, or focus only on mature firms that have been public for at least five or ten years. In explaining the trend differences, we also focus on how a spotlight effect pressures firms in the S&P 1500 to declassify rather than analyzing IPO firms use of classified boards. In this sense, our paper provides the first systematic evidence on why S&P 1500 firms have decreased their use of classified boards and contributes to

[3] Along these lines, we also broadly contribute to the literature that examines how results can change when samples are extended beyond commercial databases and to a broader set of public firms (e.g., Villalonga, 2004; Ali, Klasa, and Yeung, 2008; Cadman, Klasa, and Matsunaga, 2010; Netter, Stegemoller, and Wintoki, 2011).

studies exploring the role of investor and media attention in governance (e.g., Dyck, Volchkova, and Zingales, 2008; Liu and McConnell, 2013; Iliev, Kalodimos, and Lowry, 2021).

Finally, our paper adds to a recent literature that argues that financial economics research faces a replication crisis (e.g., Harvey, Liu, and Zhu, 2016; Linnainmaa and Roberts, 2018; Guest, 2021). We revisit a few well-known results showing how classified boards are associated with firm outcomes. Our findings suggest that for at least some studies, the appearance of a non-robust result in an extended sample period is not because the original result is not replicable, but rather it could be that the variable of interest becomes less common over time, making it difficult to detect an effect statistically. Another insight from these tests is that while some inferences are confirmed with S&P 1500 firms, different conclusions are reached for firms outside the Index.

The rest of the paper is organized as follows. Section 2 discusses our data and approach to identify whether a firm has a classified board. Section 3 examines trends in classified boards. Section 4 revisits and extends prior work on the effects of classified boards. Section 5 concludes.

2. Data and Methodology

2.1. Data sources

We use several data sources throughout our study. Our base sample starts with the CRSP-Compustat merged database from 1994 to 2020. We obtain stock return data from CRSP, accounting data from Compustat, information on analyst coverage from the Institutional Broker's Estimate System (I/B/E/S) database, and intuitional ownership from the Thomson-Reuters Institutional (13-F) Holdings database. We use the Thomson-Reuters Securities Data Company (SDC) Platinum database for information on mergers and acquisitions. 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. Appendix A provides definitions for the main variables used in our analyses.

For S&P 1500 firms, we obtain classified board information from ISS. This database tracks the classified board status of firms included in the S&P 1500 beginning in 1990, except in only 2017 when it expanded its collection to firms in the Russell 3000 Index. From 1990-2006, ISS collected data every two to three years. Beginning in 2007, ISS collected data annually. There is no backward or forward filling of data by ISS once a firm joins or leaves the S&P 1500. During the period 1996-2020, 3,611 out of 16,227 companies appear at least once in the S&P 1500, representing 22.2% of all public firms.

To implement our machine learning algorithm, we obtain all annual proxy statements (DEF 14As) from the Securities and Exchange Commission (SEC) Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system from as early as 1993. However, in our analyses, we start our samples in 1996 because this is the first year when all firms are required to file proxy statements through electronic filings on the SEC EDGAR system.

2.2. Methodology and machine learning

2.2.1. Overview of Random Forests (RF) Classifier

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

The RF Classifier methodology has been successfully used in various science fields and, recently, in the fields of economics and business. For example, RF Classifier outperforms other statistical tools in predicting future ecological changes, provides the most accurate prediction of chemical compound classifications, achieves a high degree of accuracy in 3D object recognition, and has better properties in predicting microarray data (Díaz-Uriarte and de Andrés, 2006; Prasad, Iverson, and Liaw, 2006; Svetnik et al., 2003; Shotton et al., 2013). In economics, Varian (2014) advocates the use of RF in econometrics, and Bajari, Nekipelov, Ryan, and Yang (2015) use RF to estimate demand functions. More recently, Frankel, Jennings, and Lee (2021) find RF algorithms better capture disclosure sentiment than alternative machine learning techniques.

2.2.2. Estimation steps and machine learning prediction

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

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

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

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

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

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

One of the unique features of the RF Classifier is that the algorithm provides which variables have the most predictive power. To calculate the variable importance of each predictor *i*, RF Classifier runs through the same tree but gives a random split on each node in the forests related to predictor *i*. At the end of each run, the importance of each predictor is measured as the difference in prediction performance when the specific predictor is permuted randomly so that its influence is omitted. Figure 1A tabulates the 25 phrases with the highest predictive power in determining a firm's classified board status. These 25 phrases account for 37.6% of the variable importance among the 2,287 phrases, with the top three phrases 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 of S&P 1500 firms describing the election of directors could be different than that of non-S&P 1500 firms. This possibility creates problems because our out-of-sample test validation is based on S&P 1500 firms covered by the ISS database, 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 the way non-S&P 1500 firms disclose their election process. To mitigate this concern, we perform several validity checks. First, we compare the overlap in word usage in describing the election of directors for S&P and non-S&P 1500 firms. Figure 1B shows that the fraction of S&P 1500 and non-S&P 1500 firms mentioning the 25 most important phrases, as measured by their variable importance, is very similar. As a second check, we calculate a cosine similarity value of 0.993 between the fraction of S&P and non-S&P 1500 firms using each of the 2,287 phrases, indicating that both groups use nearly identical wording.[4]

[4] In 2017, ISS collected governance data for every firm in the Russell 3000. As a third validity check, we calculate the out-of-sample error rate for the non-S&P 1500 firms in 2017 when ISS has already collected data. There are 1,118 non-S&P 1500 firms in 2017 but only 228 are in the test sample. For these 228 observations, we find eight errors.

2.2.3. Validating our classified board predictions and finalizing the dataset

Given that our application of the RF Classifier is a new approach to predicting a classified board, it is important to validate our measure and assess the out-of-sample prediction accuracy. We use three different approaches to assess the validity of our predictions, which we summarize in this section and provide details of in the Internet Appendix. First, we test the accuracy rate. As expected, the in-sample prediction accuracy is extremely high at almost 99.9%. Our out-of-sample prediction accuracy is also very high at 97.3% (with 1.5% false negatives, where our classification 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 better illustrate the power of the RF Classifier, we compare our approach to a traditional keyword search method (e.g., Karakaş and Mohseni, 2021). If we consider the keyword searches around "class" and "term" as described in the prior section and assign a classified board to any firm with these keywords, the error rate is 22.2% (21.3% false positives and 1.0% false negatives). If we refine this classification by requiring the word "class" be followed by "i", "ii", "iii", "1", "2", or "3" or preceded by "two" or "three", the error rate decreases to 8.7% (6.7% false positives and 2.0% false negatives). Modifying the keyword search this way highlights the shortcomings of keyword searches – making the search narrower to reduce false positives increases the false negatives. 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 both needing far fewer restrictive refinements and producing a lower error rate than the keyword search method. In particular, using this same text around these keywords, the RF Classifier produces a total sample error rate of 1.6%, an 81.0% (=1.64/8.68-1) improvement over the refined keyword search.

Lastly, we manually check all instances when our predictions do not match those in the ISS database and when an S&P or non-S&P 1500 firm changes its classified board status. Discrepancies between our predictions and ISS appear to arise from a few main sources. One source is that firms occasionally file the wrong document, such as a DEFM 14A related to a merger and not the annual proxy statement. A second source is that firms sometimes file a proxy statement proposing to adopt or disband a classified board, but the proposal fails. Differences also arise in a few circumstances due to the imperfect matching of firms across the databases.

The final source of discrepancy is inconsistent coding when distinguishing between when a firm votes to (de)classify its board and when the (de)classification is fully implemented, which is also an issue in the ISS data. Firms typically phase in board declassification over the few years after the proposal is approved, and these differences in the timing have implications for different analyses. For example, when examining the determinants of the decision to declassify, the relevant date is when shareholders pass the resolution, not when the board is fully declassified. In contrast, when examining the relation between firm outcomes, such as M&A decisions, the relevant period is when all directors can be replaced at the annual meeting (i.e., full implementation) because this creates the disciplining incentives. Consequently, we create two classified board indicator variables that distinguish between when firms vote to approve to (de)classify their board and when board (de)classification is fully implemented. We use the voting date for all our analyses, except in Section 4 when we reexamine prior findings on classified boards and firm outcomes.

2.3. Sample overview: Comparing S&P and non-S&P 1500 firms

While we determine whether all firms with DEF 14A filings have a classified board, in our analyses, we impose the following requirements for a firm to enter the sample: (i) the firm can be matched to CRSP, (ii) the firm has valid information for market value of equity and book value of assets, (iii) firm age based on the earliest date available on CRSP and Compustat is non-negative, and (iv) the firm's industry is not public administration and is classifiable (i.e., drop SIC codes greater than or equal to 9100). These restrictions reduce our base sample to 104,892 observations.

Figure 2A shows the number of S&P and non-S&P 1500 firms by year from 1996 to 2020. The number of S&P 1500 firms is relatively flat by construction. In contrast, the number of non-S&P 1500 firms declines over time, particularly after the dot-com bubble and through 2013. This pattern is consistent with the literature showing that the number of public firms has declined since its peak in 1996 (Doidge, Karolyi, and Stulz, 2017). Figure 2B shows that S&P and non-S&P 1500 firms have a similar distribution of firms across the nine SIC code divisions. For both samples, the top three industries are Manufacturing; Finance, Insurance, and Real Estate; and Services.

Table 1 compares key firm characteristics for S&P and non-S&P 1500 firms. For this table and later regressions, we require all firm-level variables to be non-missing. Almost all characteristics are statistically different between the samples due to S&P 1500 Index eligibility criteria related to firm size, age, profitability, and liquidity, among others. For the whole sample period, the average of the classified board indicator is 46.7% among S&P 1500 firms, which is very close to the average of 47.9% among non-S&P 1500 firms. However, as Figure 3 shows, despite having similar averages over the full sample, there is a sharp contrast in trends between the two groups over time.

Table 2 examines how key firm characteristics reported in Table 1 relate to S&P and non-S&P 1500 firms having a classified board.[5] The dependent variable, *CB*, is an indicator that equals one if a firm has a classified board, and zero otherwise. Independent variables include firm size, age, Tobin's Q, operating income, leverage, capital expenditures, R&D expenses, share turnover, return volatility, institutional ownership, analyst coverage, and whether the firm is incorporated in Delaware. We also control for industry×year and firm fixed effects in some regressions. To make the coefficients comparable across the models and because adding a large number of fixed effects to a logit or probit model creates the incidental parameters problem, we estimate linear probability models for all the specifications. In unreported tests, we find similar results using logit models.

In columns 1 and 2 of Table 2, we test how firm characteristics are related to the likelihood of having a classified board for S&P and non-S&P 1500 firms, respectively. For S&P 1500 firms, size is significantly negatively associated with having a classified board, while this relation is significantly positive for non-S&P 1500 firms. Firm age, Tobin's Q, and share turnover (the average number of analysts following the firm) are all negatively (is positively) correlated with having a classified board for both groups. Non-S&P 1500 firms incorporated in Delaware are more likely to have a classified board, but this is not the case for S&P 1500 firms. However, even though

[5] While our paper's main aim is to analyze differences in *trends* between S&P and non-S&P 1500 firms' use of classified boards, for completeness of our descriptive statistics, we correlate differences in characteristics between S&P and non-S&P 1500 firms' likelihood of having a classified board over the full sample period.

many of the coefficients are statistically significant, their combined explanatory power is low, explaining only 6.0% (4.9%) of the variation in classified boards among S&P 1500 (non-S&P 1500) firms. Column 3, which tests if the coefficient differences between columns 1 and 2 are statistically significant, indicates that nearly all the firm characteristics predicting *CB* are significantly different between the two groups.

In columns 4 and 5, we add industry×year and firm fixed effects. Including these fixed effects, which restricts estimations to within an industry-year and controls for time-invariant heterogeneity within firms shows that many of the coefficients are different in sign and significance from the models without any fixed effects. Additionally, column 6 indicates that most of the coefficient differences among S&P and non-S&P 1500 firms are not significantly different in the fixed effect models. Moreover, adding the fixed effects increases the explanatory power of the models substantially to 79.4% and 89.7%, respectively. These results suggest that over the full sample period from 1996 to 2020, having a classified board is largely a time-invariant governance policy for both S&P and non-S&P 1500 firms, irrespective of differences in the modeled characteristics.

3. Classified Boards in S&P 1500 and Non-S&P 1500 Firms

3.1. Trends in classified boards

We begin our investigation of the trends in S&P and non-S&P 1500 firms' use of classified boards in Figure 3A by plotting the fraction of firms with a classified board over time between the two groups. Consistent with prior studies, the use of classified boards was widespread among S&P 1500 firms in the late-1990s, as a majority had a classified board in 1996. This percentage exceeded 60% around 2002, before declining over the subsequent years. By 2020, less than one-third of S&P 1500 firms had a classified board. Figure 3B further shows that the declining trend is especially pronounced amongst S&P 500 firms. By 2020, only about 13% of S&P 500 firms had a classified board. The trend for non-S&P 1500 firms paints a much different picture. In 1996, roughly 40% of these firms had a classified board. This percentage gradually increased to a high of 54% by 2002 and remained relatively stable at around 50% through 2020.

What explains this sharp contrast in trends between S&P and non-S&P 1500 firms? Because Table 1 shows that many firm characteristics are significantly different between these two groups, we next investigate whether these differences drive the different classified board trends. First, we control for all firm-level variables listed in Section 2.3 (Figure 3C). Second, we add firm fixed effects (Figure 3D). By including firm fixed effects, we analyze how, for the same firm, its inclusion or exclusion from the S&P 1500 affects its likelihood of having a classified board over time. Third, we append quadratic terms for all the firm-level controls (Figure 3E). Lastly, we conduct a propensity-score matched sample analysis (Figure 3F).[6]

Collectively, the figures show that, compared to non-S&P 1500 firms, S&P 1500 firms experienced a more significant drop in the usage of classified boards over time. For example, adding firm controls has little effect on the trend differences between S&P and non-S&P 1500 firms. Further, while the contrast in trend differences becomes less striking after adding firm fixed effects, it persists nonetheless, with the percentage of S&P (non-S&P) 1500 firms with a classified board dropping roughly 80.0% (34.3%) from 1996 to 2020. A similar takeaway is found when appending quadratic terms of the firm-level controls or when using a propensity score matched sample. Thus, differences in firm characteristics, controlled for in either a parametric or non-parametric manner, cannot completely explain the trend differences in classified boards between S&P and non-S&P 1500 firms.[7]

[6] We estimate the likelihood that a firm is in the S&P 1500 using a logit model and the covariates *Ln(Assets)*, *Ln(Age)*, *Tobin's Q*, *OROA*, *Lev*, *Capex*, *R&D*, *Ln(Turn)*, *Volatility*, *IO*, *Ln(Numest)*, and *Delaware*. We then match S&P 1500 firms to non-S&P 1500 firms such that the maximum difference between their propensity scores is 0.025, they operate in the same two-digit SIC industry, and 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. We choose two matches to keep the proportion of S&P and non-S&P 1500 firms similar to that in our main sample.

[7] We also investigate whether a trend in IPO firms going public with antitakeover provisions (e.g., Johnson, Karpoff, and Yi, 2022; Field and Lowry, 2022) can explain the trend differences in classified boards between S&P and non-S&P 1500 firms. While the declining use of classified boards among S&P 1500 firms is unaffected by IPO firms, robustness tests (reported in Internet Appendix Figure IA.2.1) indicate that the trend differences is not purely an IPO effect, as our findings are similar if we include firm age fixed effects, use a propensity score matched sample that matches exactly on age, or restrict the sample to mature firms that have been public for at least five or ten years.

Figure 4 instead focuses on differences in trends in the rate that S&P and non-S&P 1500 firms declassify their boards each year.[8] Figure 4A shows that in the earlier years of our sample to around 2003, the fraction of firms that declassified their boards among S&P and non-S&P 1500 firms was very similar. The trends started to diverge after 2003 when there was a steep increase in the fraction of S&P 1500 firms declassifying their boards. Figure 4B shows an especially sharp increase in the rate that S&P 500 firms began to declassify starting from 2003, reaching its highest levels of over 30% in 2012 and 2013.[9] Figures 4C-4E show that the pattern generally persists after controlling for first- and second-order polynomials of firm characteristics and firm fixed effects. Alternatively, Figure 4F shows that differences in declassification trends between S&P and non-S&P 1500 firms are less apparent in a propensity score matched sample, although, the increasing declassification rate among S&P 1500 firms is much less noisy over time than for non-S&P 1500 firms.[10]

Overall, the inability of firm characteristics to explain away general trend differences in the use and removal of classified boards is consistent with the view that classified boards are largely a time-invariant governance policy (e.g., Gompers, Ishii, and Metrick, 2003; Johnson, Karpoff, and Yi, 2022). However, by evaluating the trends of both S&P and non-S&P 1500 firms together, we add an important nuance to the literature, showing that the increasing infrequency of the classified board structure over the past decade is predominately a feature of firms in the S&P 1500.

3.2. The spotlight effect: Attention, visibility, and scrutiny on corporate governance

Given that trends in board declassification are largely unrelated to firm-specific factors, we conjecture that a firm's inclusion in the S&P 1500 Index may contribute to the increased likelihood

[8] Internet Appendix Table IA.2 examines the determinants of board declassification for S&P and non-S&P 1500 firms. However, as we are less focused on the average effect of firm characteristics on board (de)classification over the full sample period and more interested in if there are differences in trends over time and what drives them. Therefore, we mainly view Table IA.2 as necessary to complete our overview of the descriptive statistics from Section 2.3.

[9] This evidence is consistent with reports from the Shareholder Rights Project, a Harvard Law School initiative that successfully pushed for board declassification of roughly 100 S&P 500 and Fortune 500 firms during the academic years 2011-2012 and 2013-2014.The Harvard Law School established the Shareholder Rights Project to advance the efforts of institutional investors in improving the corporate governance arrangements of publicly traded firms.

[10] For completeness, Internet Appendix Figure IA.2.2 conducts the same analysis as Figure 4 but for adopting a classified board. Overall, the trends in the fraction of firms adopting a classified board are similar for S&P and non-S&P 1500 firms, both showing a decrease in the propensity to adopt a classified board over time.

of declassifying over time. Undoubtedly, S&P 1500 firms are more intensely covered by the media, analysts, and academics and have greater institutional ownership. This public scrutiny and shareholder pressure may force these firms in the "spotlight" to adhere to good governance practices and declassify more frequently over time (e.g., Bebchuk, Cohen, and Wang, 2013; Appel, Gormley, and Keim, 2016). Indeed, boards of firms more likely to be in the spotlight often explicitly discuss in proxy statements the increased pressure and concerns from their investors regarding classified boards. For example, Skyworks Solutions' 2011 proxy statement states:

> "*The Board of Directors recognizes that a classified structure may offer several advantages, such as promoting board continuity and stability, encouraging directors to take a long-term perspective, and ensuring that a majority of the board will always have prior experience with the Company... However, the Board of Directors also recognizes that a classified structure may appear to reduce directors' accountability to stockholders, since such a structure does not enable stockholders to express a view on each director's performance by means of an annual vote. Moreover, many institutional investors believe that the election of directors is the primary means for stockholders to influence corporate governance policies and to hold management accountable for implementing those policies.*"[11]

To investigate the "spotlight effect", we first examine whether firms that previously had a classified board are more likely to drop this board structure after joining the S&P 1500. Second, we investigate how media and academic attention to corporate governance and classified boards have changed over time. Finally, we consider changes in the composition of a firms' investor base and their role in proposing and facilitating board declassification.

3.2.1. S&P 1500 membership and board classification

We begin our exploration of the spotlight effect by examining if the likelihood of having a classified board changes after a firm joins the S&P 1500 and whether this effect changes over time. To conduct this test, we set up a stacked difference-in-difference analysis in which a firm joining the Index is considered a treatment event. We use a similar propensity score matching procedure as that in Figure 4D 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. We require both groups to have a classified board in

[11] https://www.sec.gov/Archives/edgar/data/4127/000104746911003377/a2203251zdef14a.htm.

the years before treatment and keep the ±3 years around the treatment year.[12] We limit our analysis to firms joining the S&P 1500 between 1999 and 2017 to allow for three full years of data before and after treatment. We then regress our classified board dummy variable on timing dummies that indicate the year relative to the treatment year, firm fixed effects, and other controls. To examine how the effect of joining the S&P 1500 on having a classified board changes over time, we split the sample into four cohorts: 1999-2003, 2004-2008, 2009-2013, and 2014-2017. The cohort labels signify that the firm was added to the Index in one of these cohort years. For example, if a firm joined the S&P 1500 in 2017, the firm and its corresponding matched firms would be included in the 2014-2017 cohort and have sample years of 2014-2020 included in the regression.

Figures 5A and 5B plot the coefficients from these regressions without and with firm-level controls, respectively. Both figures show statistically significant estimates in the later 2009-2013 and 2014-2017 cohorts. For these two cohorts, the figures show that in the three years after joining the Index, S&P 1500 firms are significantly less likely to keep a classified board. In contrast, S&P 1500 firms in the 1999-2003 and 2004-2008 cohorts are equally likely to maintain their classified boards as the control firms. Overall, this evidence is consistent with a spotlight effect on S&P 1500 firms being particularly intense during the latter part of the sample and aligns with the decreasing trend in classified boards among these firms shown in our prior figures.

3.2.2. Rise of attention from the news media and academics

We next investigate whether trends in news media and academic attention on corporate governance and classified boards are consistent with a spotlight effect that pressures S&P 1500 firms to declass their boards over time. The Enron and WorldCom accounting scandals in the early 2000s damaged investor confidence and brought to light a widespread lack of internal controls and effective governance structures in major U.S. firms. In 2002, the U.S. Congress passed the

[12] 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. This requirement results in 684 treatment-firms and 23,810 control-firm-year observations. After applying the same matching scheme as in Figure 4D, our matched sample has 390 treatment firms and 677 control firms.

Sarbanes-Oxley (SOX) Act to protect investors from fraudulent financial reporting. These scandals and the corresponding regulatory response received substantial news coverage. Figure 6A shows this spike in news media attention. Prior to 2001, the WSJ published fewer than 200 articles each year covering topics related to corporate scandals, fraud, and misconduct. Coverage of these topics sharply increased in 2002 to over 1,000 articles, clearly reflecting heightened attention to governance, particularly among large, prominent firms. After reaching its peak in 2002, WSJ coverage of these topics gradually declined, returning to its pre-SOX level by 2010. Since then, the number of articles related to these topics has remained at fewer than 200 per year.

Along with the heightened attention to corporate scandals after the infamous Enron and WorldCom events, the news media also started paying more attention to corporate governance and shareholder activism. Figure 6A also shows that the number of WSJ articles mentioning corporate governance and shareholder activism increased from less than 20 in the late 1990s to roughly 80 in 2002. However, unlike the coverage of corporate scandals, the media's attention to governance and activism has remained relatively high through 2020.

In addition to increasing media attention to governance-related issues, Figure 6B shows a steady rise in academic attention to classified boards. The number of Google Scholar articles that mention classified boards has increased over tenfold from only 42 articles in 1996 to 463 in 2020. Because these papers might not focus on classified boards, we also apply a strict filter requiring that a paper's title mention classified boards. While there are fewer of these articles, there is still an upward trend in academic attention on classified boards, averaging less than one article per year in the first five years of the sample to almost seven articles per year in the last five years. Finally, we conduct a similar analysis for papers posted on the Social Sciences Research Network (SSRN), which allows us to count articles that mention classified boards in the paper's title, abstract, or keywords. Like the Google Scholar results, the number of SSRN articles averaged one article per year in the first five years and almost nine articles per year in the last five years.

Overall, we document a steady rise in media attention to corporate governance issues and academic attention to classified boards, consistent with Bebchuk, Cohen, and Wang (2013) who find a structural increase in media and academic attention paid to governance around 2001. They also find that market participants' learning to appreciate the value differences between well- and poorly-governed firms led to the relation between abnormal stock returns and S&P 1500 firms' governance indices in the 1990s (Gompers, Ishii, and Metrick, 2003; Bebchuk, Cohen, and Ferrell, 2009) disappearing by the 2000s. We conjecture that the increased attention to governance likely has a different impact on S&P versus non-S&P 1500 firms. Prior studies show that firms directly covered or implicated in scandals by news media face greater pressure to change, whereas firms overlooked by the press are less motivated to do so (Farrell and Whidbee, 2002; Dyck, Volchkova, and Zingales, 2008; Wiersema and Zhang, 2013). Consistent with our hypothesized spotlight effect, given that both news media and academic research primarily focus on S&P 1500 firms, the increased pressure on these prominent firms is consistent with the differences in trends in board declassification among S&P versus non-S&P 1500 firms.

3.2.3. Rise of attention from investors

Another important trend that is likely associated with increased shareholder pressure to improve governance and eliminate classified boards is the rise in institutional ownership. For instance, after the Enron and WorldCom scandals, Patrick McGurn (special counsel to ISS), commented that, in its proxy voting advisory role to institutional investors, "ISS often receives inquiries as to [its] views on the two or three governance changes that…would help investors to avoid similar market meltdowns in the future," and that, "unquestionably, the item on [its] wish list…is the call for annual elections of all members of corporate boards" (McGurn, 2002).

Especially important in this context is the rise of index funds. Index funds are passive owners that own a certain amount of a firm's shares in accordance with their benchmark weights. Investors can exert influence when they do not agree with a firm's governance structures by selling shares (i.e., "The Wallstreet Walk"), actively engaging with managers in private communications, or filing shareholder proposals (e.g., Shleifer and Vishny, 1986; McCahery, Sautner, and Starks, 2016). By the nature of their charter and the need to reduce tracking error, index funds are mostly barred from the first strategy and must engage with managers 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).[13]

To get a sense of how institutional ownership has changed over time, Figure 7A plots the average amount of shares owned by 13-F institutional investors for S&P and non-S&P 1500 firms between 1996 and 2020. Figure 7B is similar, except that we limit institutional investors to quasi-indexers, defined using the classifications from Bushee and Noe (2000) and Bushee (2001), which are investors characterized by low portfolio turnover and diversified holdings. The sample for this figure is from 1996 to 2018 due to the availability of the investor classifications. Figure 7C plots the average amount of shares owned by the Big Three index fund managers.

Not surprisingly, due to inclusion in a major stock index and mandatory reporting requirements around the 5% ownership mark that creates barriers for large institutions to obtain a meaningful stake in smaller firms, Figure 7 shows that S&P 1500 firms have higher total, quasi-index, and Big Three institutional ownership than non-S&P 1500 firms. Figure 7A shows that in 1996, total institutional ownership for S&P 1500 firms averaged 50.6%, plateauing around 2007 at 82.3% and staying near 80% since. For non-S&P 1500 firms, total institutional ownership averaged 22.3% in 1996, remaining between 40% and 50% since the mid-2000s, and only peaking in 2020 at 50.1%.

The pattern for quasi-index ownership in Figure 7B is consistent with increasing index ownership likely forcing investors to engage with managers to improve governance. For S&P 1500 firms, quasi-indexer ownership was 24.2% in 1996 and only 27.2% in 2002 before it increased sharply over the next few years to 62.7% in 2006. This rise in index fund ownership corresponds to when firms in the S&P 1500 began to decrease their use of classified boards substantially. There was also an increase in quasi-indexer ownership for non-S&P 1500 firms, but it never reached the levels of that of S&P 1500 firms. Ownership was only 8.4% in 1996, before rising to 14.0% in 2003 and peaking at 29.2% in 2007.

Lastly, Figure 7C shows the substantial and continuing growth of Big Three ownership of S&P 1500 firms. In 1996, the Big Three owned a very small percentage of S&P and non-S&P firm

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

shares. By 2020, Big Three ownership increased to about 25% for S&P 1500 firms and 10% for non-S&P firms, with ownership of S&P 1500 firms rapidly increasing after 2008. Importantly, for our later analysis of voting on proposals to declassify, while many shareholders do not vote, the Big Three tend to vote all their shares (Hirst and Bebchuk, 2019; Griffin, 2020).

Overall, disproportionate rises in attention among the news media and academics and ownership stakes by institutional investors of S&P 1500 firms is consistent with our hypothesis that these firms' corporate governance policies have become increasingly under the scrutiny of the spotlight that in part leads to increased pressure to declassify their boards.

3.2.4. Change in sentiment towards classified boards

Given our findings that institutional ownership in general and quasi-indexer and Big Three ownership in particular steadily increased over time and at a faster rate for S&P 1500 firms, we investigate whether changes in index funds' attitudes toward classified boards over time can explain some of the trend differences between S&P and non-S&P 1500 firms' use of classified boards. To do so, we first regress our classified board indicator on quasi-indexer and non-quasi-indexer ownership interacted with year dummy variables. Figure 8A plots the coefficients on these interaction terms. During the late-1990s, the coefficients on quasi-indexer ownership are positive and significant, suggesting that quasi-indexers are pro-management and support classified boards. This sentiment becomes more neutral in the mid-2000s and shifts permanently, turning significantly negative after 2010. The pattern is similar but more muted for non-quasi-indexers.

Figure 8B is similar, except that we regress the classified board indicator on Big Three and non-Big Three ownership interacted with year dummies. Compared to quasi-indexers, the change in sentiment towards having a classified board among the Big Three is even more drastic, consistent with the observation that all three of these fund managers have policies to generally vote in favor of board declassification (Bebchuk, Hirst, and Rhee, 2013).

To get a "back-of-the-envelope" sense of how much the change in the level and attitudes of quasi-indexers and the Big Three contributed to the decline in the use of classified boards, Figures 8C and 8E plot the average predicted values from the regressions in 8A and 8B, respectively. By construction, these figures show a very similar pattern to our main result. Classified board use among S&P 1500 firms remains high and flat throughout the early 2000s before dropping dramatically beginning in the mid-2000s. From peak to trough, the fraction of firms with a classified board in Figure 8C (8E) drops from 58.7% to 32.3% (59.2% to 31.9%).

In Figures 8D and 8F, we plot the average predicted values from these same regressions after setting quasi-indexer and Big Three ownership to zero, respectively. Without allowing any effect of quasi-indexer or Big Three ownership on the use of classified boards, changes in firm characteristics have a much more subdued effect on the trends. Especially for S&P 1500 firms, the figures show a smaller decline in the fraction of firms having a classified board. From peak to trough, the fraction of S&P 1500 firms with a classified board in Figure 8D (8F) drops from 53.2% to 38.8% (54.2% to 40.9%). Moreover, restricting the effect of quasi-indexer and Big Three ownership from varying by year substantially worsens the explanatory power of the predictions of the actual trends in S&P 1500 firms' use of classified boards. Compared to the R^2 values from regressing the actual yearly averages of classified board use on the predictions from Figures 8C and 8E, the predictions from the models in Figures 8D and 8F explain 20.3% (=0.795/0.998-1) and 9.1% (=0.900/0.999-1) less of the variation in the actual trends, respectively.

Overall, Figures 7 and 8 indicate that quasi-indexer and Big Three ownership of S&P 1500 firms has risen over time, especially in the latter half of the sample, and that ownership by these investors during a similar time span associates negatively with board classification. Further, changes in the level of ownership and attitudes towards classified boards by these groups of investors contributes significantly to the trend differences between S&P and non-S&P 1500 firms. These findings are further supportive of the spotlight hypothesis. We next examine whether this pressure and shift in sentiment against classified boards ultimately culminates in an increase in and support for shareholder proposals demanding board declassification.

3.2.5. Shareholder proposals to declassify boards

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

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

Figure 9A plots the fraction of firms voting on all proposals to declassify their boards over time, while Figure 9B breaks down this fraction into shareholder- and manager-sponsored proposals.[14] Although we are interested in shareholder pressure to declassify boards, which shareholder-sponsored proposals unambiguously capture, managers may put forward their own proposals at the request of shareholders. They do this because investors frequently engage in behind-the-scenes interventions through private negotiations with management and take public measures such as shareholder proposals only if these private interventions fail (McCahery, Sautner, and Starks, 2016). Therefore, the frequency of manager-sponsored proposals may also be indicative of shareholder pressure.

[14] When calculating the fraction of firms receiving a proposal to declassify their board, we only include firms that have a classified board in either year *t* or *t*-1.

Overall, Figure 9 is consistent with the spotlight effect hypothesis. Figure 9A shows that the fraction of firms that receive a proposal to declassify is always higher for S&P 1500 firms. S&P 1500 firms are, on average, more than five times as likely to receive a proposal to declassify, with these magnitudes spiking in 2006, 2008, 2012, and 2020. This finding suggests that for S&P 1500 firms, investors put more effort into monitoring management and are more actively engaged in proposing changes to influence governance. In contrast, investors in non-S&P 1500 firms are more passive and much less likely to propose changing a firm's governance structure. The figure also shows a substantial increase in the fraction of S&P 1500 firms receiving a proposal from 2003 through 2012, which corresponds to the large drop in the fraction of firms with a classified board shown in previous figures.

When we separate shareholder- and management-sponsored proposals in Figure 9B, the patterns are similar. The main difference is that beginning around 2012, the increase in proposals is dominated by management-sponsored proposals. This shift in sponsorship composition could be consistent with managers learning about shareholders' desire to declassify through private communications or being less resistant to shareholder proposals to declassify following the Harvard Law School's Shareholder Rights Project's initiative to push for board declassification.

Figure 10 further examines the success rate of these proposals. Figure 10A plots the fraction of declassification proposals that receive majority support and pass, while Figure 10B breaks the pass rates down by sponsor type. Among S&P 1500 firms, proposals are slightly more likely to pass, with average passing rates of 81.8% and 79.4% for S&P and non-S&P 1500 firms, respectively. For S&P 1500 firms, the rate that shareholder-and manager-sponsored proposals pass is similar at 81.5% and 82.2%, respectively. In contrast, shareholder-sponsored proposals at non-S&P 1500 firms are substantially less likely to pass compared to manager-sponsored proposals, with pass rates of 59.4% and 85.7%, respectively.

Figures 10C-10F examine trends in shareholder support in terms of voting outcomes. Figures 10C and 10D plot the average percentage of votes cast in favor of declassifying a board across all proposals and broken down by sponsor type, respectively. By focusing on voting percentages instead of whether a proposal passes, we can better understand how shareholder sentiment towards declassifying boards changes over time. Because voting percentages include votes by external shareholders and insiders, in Figures 10E and 10F, we plot the average fraction of mutual funds that vote in favor of declassifying a board across all proposals and by sponsor type, respectively.

Overall, there is a steady increase in the average voting support of proposals to declassify for S&P 1500 firms, especially for shareholder-sponsored proposals. In 2003, only 69.8% of votes were cast in favor of declassifying, whereas this fraction increased to 95.4% in 2020. Similarly, the fraction of mutual funds supporting declassification increased from 90.5% at the beginning of our sample to 98.7% by the end. Again, these trends are largely driven by increased support among shareholder-sponsored proposals, while support for management-sponsored proposals was in the upper 90%s for all years for both S&P and non-S&P 1500 firms. While there is also an increasing trend in shareholder support to declassify boards among non-S&P 1500 firms, the trends are much less stark and more volatile.

In sum, the results in Figures 9 and 10 suggest that shareholders of non-S&P 1500 firms are less active in proposing changes to board structure, and when they do take such actions, they are less likely to succeed. Our interpretation is that compared to active shareholders in non-S&P 1500 firms, those in S&P 1500 firms are likely more experienced, have better resources, and are more effective at coordinating with fellow shareholders to gain majority support for their proposals. The higher success rate among S&P 1500 firms is also consistent with Appel, Gormley, and Keim (2019) and Brav, Jiang, Li, and Pinnington (2021) who find that activists are more likely to target firms when they anticipate fellow shareholders to be more supportive (e.g., when firms have a higher fraction of passively managed fund ownership). Therefore, both the lack of enthusiasm in proposing a change and the low success rate appear to contribute to the lower fraction of non-S&P 1500 firms declassifying their boards.

Taken together, the results in Section 3.2 are consistent with a spotlight effect that increases over time and places the governance policies of S&P 1500 firms under more intense scrutiny, ultimately culminating in concerted pressure from shareholders to declassify (e.g., Belinfanti, 2008; Dyck, Volchkova, Zingales, 2008; Appel, Gormley, and Keim, 2016; McCahery, Sautner, and Starks, 2016; Abramova, Core, and Sutherland, 2020).

3.3. Trends in M&A activity

Another possible explanation for the difference in trends in board classification between S&P and non-S&P 1500 firms relates to differences in trends in M&A activity. For example, during the latter half of our sample period, if firms outside the S&P 1500 were more likely to be targeted for acquisition than firms in the Index, then their need for a classified board as a takeover defense would have also increased during those sample years relative to that of S&P 1500 firms. We investigate this explanation in Figure 11 by plotting the likelihood that firms in the S&P and non-S&P 1500 are targeted for a takeover by year. The figure shows that the trend in M&A activity across the groups of firms is similar over the full sample period, with or without controlling for firm characteristics and industry fixed effects. Therefore, differences in M&A trends between S&P and non-S&P 1500 firms seem unlikely to explain the differences in trends in classified boards.

4. Revisiting and Extending Prior Findings

We next examine whether previously documented associations between classified boards and acquisition performance, earnings management, and firm value are similar for S&P and non-S&P 1500 firms. Recognizing that having a classified board is an endogenous choice, our goal for this section is to only confirm whether there are differences in prior findings between S&P and non-S&P 1500 firms, setting aside causal explanations of any differences for future work.

4.1. Classified boards and acquisition returns

We replicate the key results in Masulis, Wang, and Xie (2007), who document that acquirers with a classified board have significantly lower announcement returns, suggesting that firms with classified boards are more likely to indulge in empire-building acquisitions that destroy shareholder value (e.g., Jensen, 1986). Following their methodology, we first use the ISS sample from 1990 to 2003 and test the relation between having a classified board and acquirer M&A announcement returns in column 1 of Table 3. Consistent with their results, the coefficient on *CB* is negative and statistically significant at the 5% level. Using the same dataset, we present the result for deals announced from 1996 to 2003 in column 2 because 1996 is the first year we have complete DEF 14A filings. The results are similar, except that the coefficient on *CB* is only marginally significant at the 10% level in a one-tailed *t*-test, which could be driven by a lack of power due to a smaller sample.

In column 3, we extend the ISS sample from 1996 to 2020. We also include institutional ownership, analyst coverage, and firm age as controls. The coefficient on *CB* is close to zero and statistically insignificant. In column 4, we repeat the analysis using only S&P 1500 firms and find a similar result.[15] The insignificant coefficient on *CB* for the extended sample period might suggest that the classified board structure is less detrimental to shareholder wealth in the more recent period. Alternatively, the insignificant relation could result from classified boards becoming scarcer among S&P 1500 firms in recent years, rendering it challenging to detect an effect.

To distinguish the two alternative explanations, in column 5, we focus on the non-S&P 1500 sample for which we show that the percentage of firms with a classified board is more common and stable over time. In contrast to the ISS and S&P 1500 results over the extended sample and in support of the second explanation, the coefficient on *CB* is negative and statistically significant among non-S&P 1500 bidders from 1996 to 2020 (coeff=-0.433, *t*-stat=-2.06). This result supports the entrenchment view of classified boards as argued in Masulis, Wang, and Xie (2007), particularly because when firms are not in the spotlight that comes with S&P 1500 inclusion during the latter part of the sample, fewer monitors are keeping entrenched managers in check.

4.2. Classified boards and earnings management

Given the link between corporate governance and accounting fraud, we next revisit the key result in Zhao and Chen (2008), who document that classified boards are associated with less earnings management. The authors' interpretation is that classified boards enable managers to enjoy the quiet life (e.g., Bertrand and Mullainathan, 2003), and as a consequence, they are not motivated to manage earnings. We investigate whether this documented negative relation holds in our extended sample of S&P and non-S&P 1500 firms. Table 4 presents the results.

As in Zhao and Chen (2008), column 1 focuses on the ISS sample from 1995 to 2001 and shows a negative and statistically significant relation (coeff=-0.005, *t*-stat=-2.12) between having

[15] The difference between the ISS sample and the S&P 1500 sample is that ISS included Russell 3000 firms in 2017.

a classified board and the absolute value of discretionary accruals. Column 2 extends this sample from 1996 to 2020 and shows that the association between *CB* and earnings managements becomes stronger statistically (coeff=-0.003, *t*-stat=-2.86). Column 3 repeats the analysis but uses only S&P 1500 firms and shows a more pronounced effect (coeff=-0.004, *t*-stat=-3.37). Conversely, in column 4, when focusing on non-S&P 1500 firms over the same period, the association between *CB* and earnings management is statistically insignificant (coeff=-0.002, *t*-stat=-1.51). Thus, while firms in the S&P 1500 with classified boards appear less inclined to manage earnings, a similar effect does not hold for non-S&P 1500 firms, which could be consistent with the accounting practices of S&P 1500 firms being under more intense scrutiny via the spotlight effect.

4.3. Classified boards and firm value

Prior studies that focus only on firms in the ISS sample find nuanced results on the association between classified boards and firm value. For example, Faleye (2007) shows that classified boards are negatively correlated with Tobin's Q in the cross section, arguing that classified boards destroy firm value by shielding inefficient managers from the disciplining effect of the market for corporate control (e.g., Jensen, 1988). In contrast, Cremers, Litov, and Sepe (2017) find that having a classified board is positively associated with Tobin's Q in the time series, reasoning that a classified board creates value by enabling a firm to commit to long-term business plans and bonding the firm to the relationship-specific investments of its stakeholders (e.g., Stein, 1988, 1989; Johnson, Karpoff, and Yi, 2015). We investigate whether these documented associations prevail in our extended sample of S&P and non-S&P 1500 firms. Table 5 presents the results.

Column 1 revisits the specification and findings in Faleye (2007). Focusing on the ISS sample from 1995 to 2002 and including a similar set of firm-level controls and industry and year fixed effects, we find a negative and statistically significant relation between classified boards and Tobin's Q (coeff=-0.109, *t*-stat=-2.42). Column 2 uses the period 1996-2020, includes additional firm-level controls, and uses more stringent industry×year fixed effects. The results show that the negative association holds (coeff=-0.071, *t*-stat=-2.83). Columns 3 and 4 interchange the ISS sample for our dataset that covers S&P and non-S&P 1500 firms, respectively. The results show that the negative relation between having a classified board and Tobin's Q is more pronounced in the extended sample, especially for non-S&P 1500 firms (coeff=-0.112, *t*-stat=-4.51).

With the cross-sectional result of the prior study confirmed, we turn to the time-series result documented in Cremers, Litov, and Sepe (2017). Using the same expanded sample but adding firm fixed effects, column 5 shows that classified boards are positively and statistically significantly related to Tobin's Q for S&P 1500 firms (coeff=0.090, *t*-stat=2.30). Conversely, this conclusion does not hold for non-S&P 1500 firms, as the coefficient on *CB* is negative and statistically insignificant (coeff=-0.024, *t*-stat=-0.47). Overall, the results in Table 5 confirm the findings in prior studies and add novel evidence that classified boards are value reducing in the cross section and value irrelevant in the time series for firms outside the S&P 1500.

5. Conclusion

Whether classified boards are beneficial or detrimental to firms remains an ongoing debate in the literature. However, descriptive evidence on classified boards suggests that this debate may be becoming a moot point as a large number of firms have already declassified their boards, leading many to conclude that classified boards are heading towards endangered status. We argue that the evidence behind this conclusion is incomplete because it is based only on the observed trends of the most prominent U.S. firms and, hence, missing information on the majority of public firms.

The primary obstacle preventing more complete inferences on whether classified boards are becoming rare is the lack of coverage by commercial databases. For example, the most common source for classified boards, the ISS Governance database, is limited to firms included in the S&P 1500 Index. We overcome this limitation by implementing a machine learning technique, the Random Forests Classifier, along with textual analysis and manual inspection to construct a new dataset that contains the classified board status of all U.S. public firms between 1996 and 2020.

With this new dataset, we present three key findings. First, while S&P 1500 firms are becoming less likely to have a classified board (about 30% of firms in 2020, equaling a near 50% reduction since 1996), roughly half of all non-S&P 1500 firms maintain classified boards in 2020 (about a 35% increase since 1996). Differences in firm characteristics between S&P and non-S&P 1500 firms cannot explain these divergent trends. Second, we find suggestive evidence that a "spotlight effect" at least partially explains the trend differences, as the visibility of being in the S&P 1500 increases the scrutiny market participants place on firms to declassify their boards. For example, compared to non-S&P 1500 firms with classified boards, S&P 1500 firms are over five times more likely to vote on proposals calling for declassification. We also find that in the period when the spotlight brightens, firms that are added to the S&P 1500 become significantly less likely to maintain their classified boards.

Lastly, we revisit a few prominent studies on classified boards and firm outcomes that focus only on S&P 1500 firms and find some differences for non-S&P 1500 firms. For instance, while the negative relation between classified boards and bidder M&A announcement CARs has dampened over time for S&P 1500 firms, it remains negative and statistically significant for non-S&P 1500 firms. We also show that while a negative association between classified boards and Tobin's Q in the cross section is similar for firms included and excluded from the S&P 1500, a significant positive association in the time series is only observed for S&P 1500 firms, whereas the sign remains negative but statistically insignificant for non-S&P 1500 firms.

Overall, our paper provides novel evidence indicating that classified boards are not becoming an endangered species. Rather, they are alive and well, hiding in plain sight among firms not covered by commercial databases. This finding offers several implications for future work. In particular, it suggests that the debate on classified boards has not become a moot point. Quite the opposite. It implies that more research is necessary to revisit and expand on prior work that focused solely on firms in the ISS database (that compose a relatively small subset of the universe of public firms) for which specific findings might be altered. Additionally, from a methodological contribution, we show how advances in machine learning coupled with existing commercial databases can be used to create new comprehensive datasets that offer many opportunities for future research.

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Appendix A. Variable Definitions

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

Variable	Definition (Compustat and CRSP variables are in italics when appropriate)
Age	One plus the number of years that a firm has been publicly traded, determined based on the earliest date the firm has non-missing returns in the CRSP or Compustat databases.
All Cash	Indicator variable equal to one if the bidder used only cash to pay for the acquisition, and zero otherwise.
Assets	Book value of assets (*at*) (in millions and 2017 dollars).
Big Three IO	Percentage of a firm's shares outstanding owned by the big three (i.e., Blackrock, State Street, and Vanguard) institutional investors at the end of a firm's fiscal year.
Capex	Capital expenditure divided by book value of assets (*capx/at*).
CAR (-2, +2)	Bidder cumulative abnormal returns over the five-day window surrounding the acquisition announcement date, where the announcement date is day zero. The abnormal return is net of the market return, proxied by the CRSP value-weighted index.
CB	Indicator variable equal to one if a firm has a classified board, and zero otherwise.
Declassify	Indicator variable equal to one if a firm has a classified board in year *t* and not a classified board in year *t*+1, and zero otherwise.
Delaware	Indicator variable that equals one if a firm is incorporated in Delaware, and zero otherwise.
Diversify	Indicator variable equal to one if the bidder and target are not in the same two-digit SIC industry, and zero otherwise.
EM	Absolute value of discretionary accruals. Discretionary accruals are estimated using the Jones model by two-digit SIC industry each year and performance-matching following Kothari, Leone, and Wasley (2005).
IO	Percentage of a firm's shares outstanding owned by institutional investors at the end of a firm's fiscal year.
Lev	Value of debt in current liabilities plus long-term debt scaled by book value of assets [(*dlc*+*dltt*)/(*at*)].
MVE	Market value of equity at the end of the fiscal year (*prcc_f***csho*) (in millions and 2017 dollars).
Numest	Average number of analysts following a firm over its fiscal year.
OROA	Operating income before depreciation scaled by book value of assets (*oibdp/at*).
Private Target	Indicator variable equal to one if the target is a private company, and zero otherwise.
Public Target	Indicator variable equal to one if the target is a public company, and zero otherwise.
Quasi-Indexer IO	Percentage of a firm's shares outstanding owned by quasi-indexer institutional investors at the end of a firm's fiscal year, as defined in Bushee (2001) and Bushee and Noe (2000).
R&D	Research and development expenses scaled by book value of assets (*xrd/at*). *xrd* is set to zero when missing.
Relative Size	Ratio of M&A deal value to the bidder's market value of equity on the 11^{th} trading day before the deal announcement day.

Runup	A firm's buy-and-hold return over the [-210,-11] trading days before a deal announcement minus the buy-and-hold return on the CRSP value-weighted index over the same period.
Tech	Indicator variable equal to one if the bidder and target are both from high tech industries, and zero otherwise. High tech industries are defined as those in SIC codes 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677, 3678, 3679, 3812, 3823, 3825, 3826, 3827, 3829, 3841, 3845, 4812, 4813, 4899, 7371, 7372, 7373, 7374, 7375, 7378, and 7379.
Tender	Indicator variable equal to one if SDC reports that the deal is a tender offer, and zero otherwise.
Tobin's Q	Market value of assets (*prcc_f*csho+at-ceq*) scaled by book value of assets (*at*).
Turn	Average monthly share turnover over a firm's fiscal year. Share turnover is defined as trading volume divided by the total number of shares outstanding.
Stock Deal	Indicator variable equal to one if the bidder used some stock to pay for the acquisition, and zero otherwise.
Volatility	Standard deviation of monthly returns over a firm's fiscal year.

Appendix B. 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[16]

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.

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

Figure 1
Variable Importance and N-Gram Overlap

Figure A tabulates the variable importance values of the top 25 N-Grams that predict a firm's classified board status. Figure B tabulates the fraction of firms mentioning the specific N-Gram.

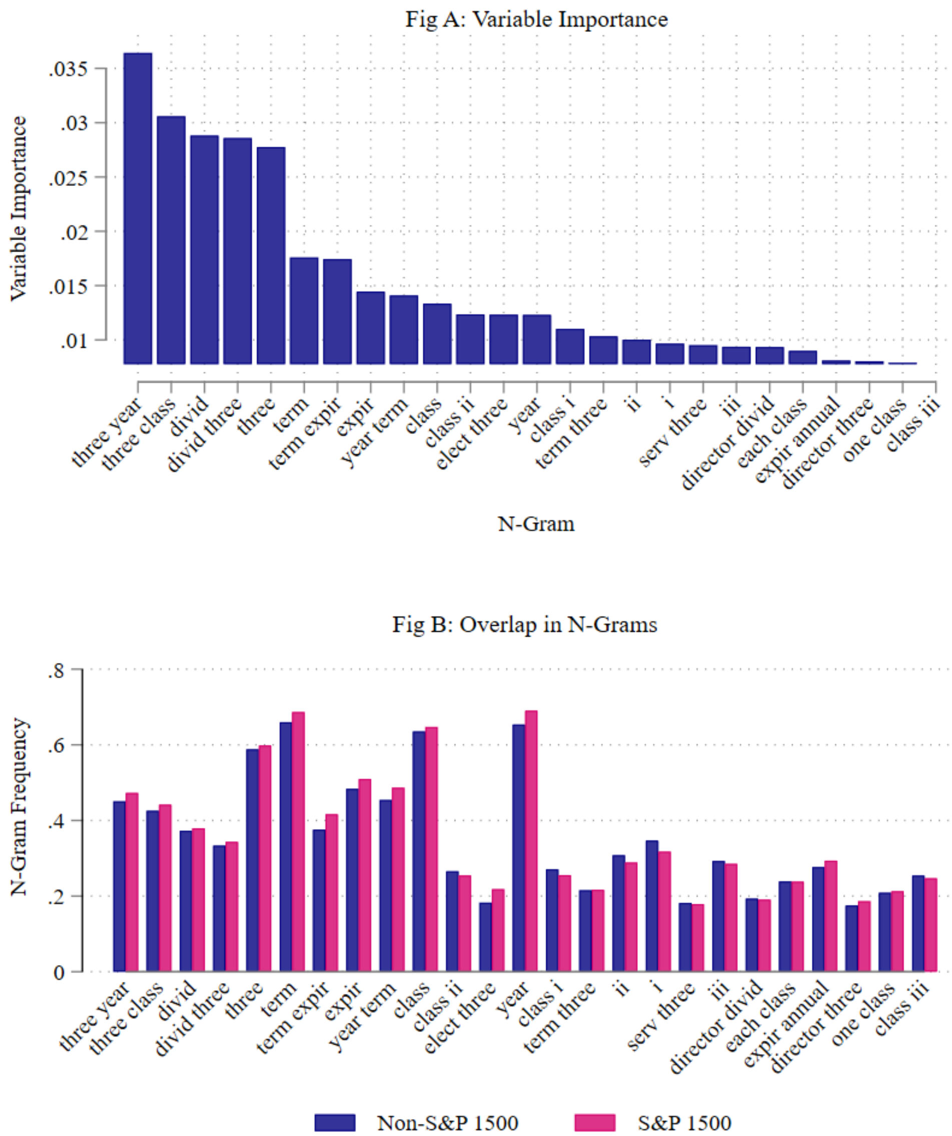

Figure 2
Distribution of Firms by Year and SIC Code Division

Figure A tabulates the number of S&P 1500 and non-S&P 1500 firms by year between 1996 and 2020. Figure B tabulates the fraction of S&P 1500 and non-S&P 1500 firms by SIC code divisions between 1996 and 2020. The divisions are: Agriculture, Forestry, and Fishing (0100-0999); Mining (1000-1499); Construction (1500-1799); Manufacturing (2000-3999); Transportation, Communications, Electric, Gas and Sanitary Service (4000-4999); Wholesale Trade (5000-5199); Retail Trade (5200-5999); Finance, Insurance, and Real Estate (6000-6799); and Services (7000-8999).

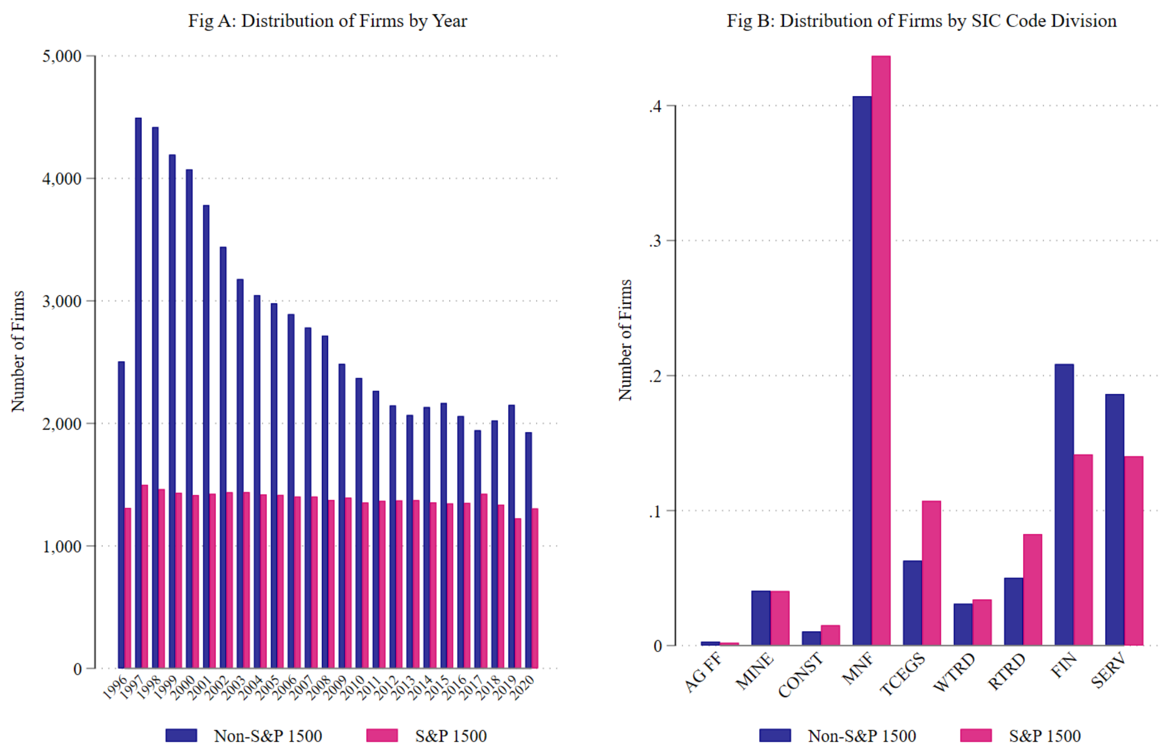

Figure 3
Fraction of Firms with a Classified Board

Figures A and B tabulate the fraction of firms with a classified board by year. Figure C controls for the same set of firm-level variables as in Table 2. Figure D further controls for firm fixed effects. Figure E controls for firm fixed effects and quadratic terms of the controls in Figure C. Figures C-E plot the coefficient estimates (β_{1996}-β_{2020} and ω_{1996}- ω_{2020}) from their respective versions of the following OLS regression of the classified board indicator (*CB*) on controls, where *SP* and *NonSP* are dummy variables indicating whether a firm is in the S&P 1500 Index or not:

$$CB_{it} = \sum_{t=1996}^{2020} (\beta_t Year_t \times SP_{it} + \omega_t Year_t \times NonSP_{it}) + \Gamma X_{it} + \gamma_i + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year *t*, and zero otherwise. X_{it} are firm-level characteristics, and γ_i are firm fixed effects. Figure F first matches S&P 1500 to non-S&P 1500 firms by estimating a propensity score based on the same firm-level characteristics as in Figure C and further matching exactly on two-digit SIC industry and year.

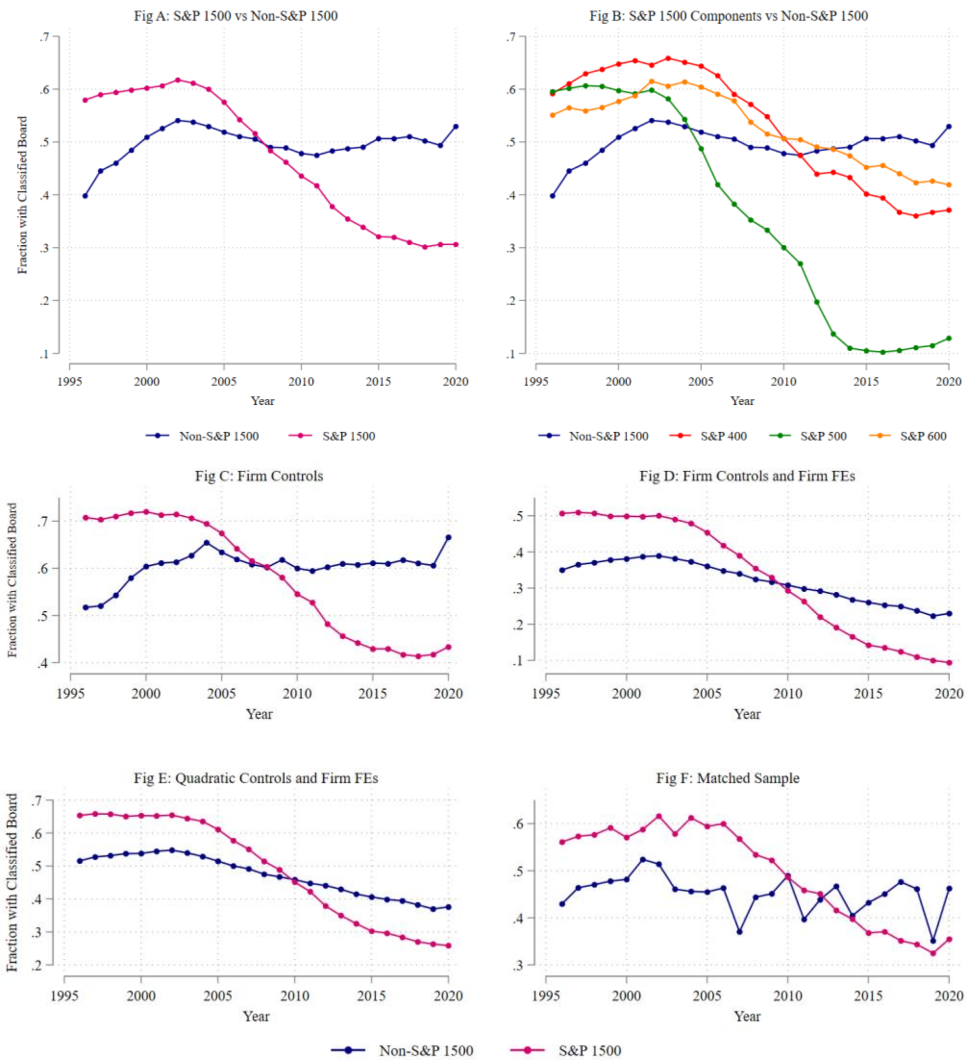

Figure 4
Fraction of Firms Declassifying Boards

Figures A and B tabulate the fraction of firms declassifying their board by year. Figure C controls for the same set of firm-level variables as in Table 2. Figure D further controls for firm fixed effects. Figure E controls for firm fixed effects and quadratic terms of the controls in Figure C. Figures C-E plot the coefficient estimates (β_{1996}-β_{2020} and ω_{1996}- ω_{2020}) from their respective versions of the following OLS regression of the declassify indicator (*Declass*) on controls, where *SP* and *NonSP* are dummy variables indicating whether a firm is in the S&P 1500 Index or not:

$$Declass_{it} = \sum_{t=1996}^{2020} (\beta_t Year_t \times SP_{it} + \omega_t Year_t \times NonSP_{it}) + \Gamma X_{it} + \gamma_i + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year t, and zero otherwise. X_{it} are firm-level characteristics, and γ_i are firm fixed effects. Figure F first matches S&P 1500 to non-S&P 1500 firms by estimating a propensity score based on the same firm-level characteristics as in Figure C and further matching exactly on two-digit SIC industry and year.

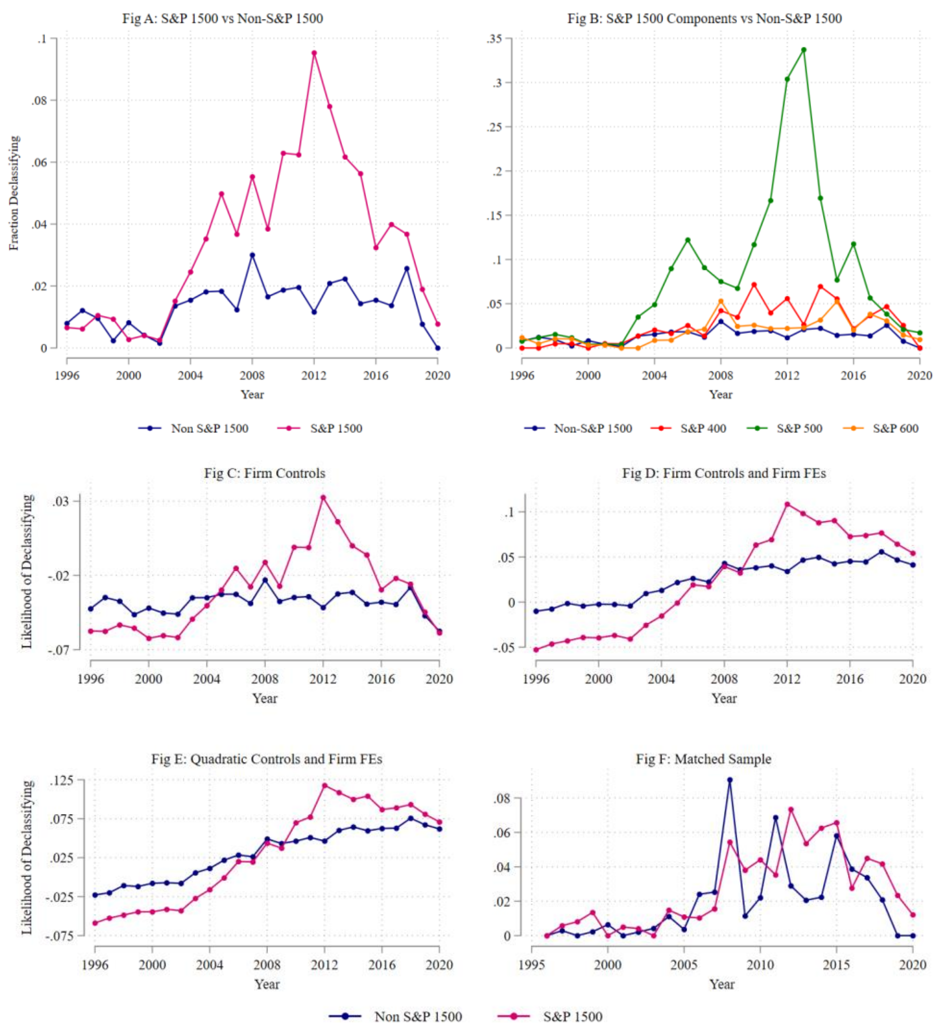

Figure 5
Effect of Joining the S&P 1500 on Having a Classified Board by Time Period

This figure plots the coefficient estimates (β_{-3}- β_3) from an OLS regression on a propensity score matched sample examining the effect of joining the S&P 1500 on the likelihood of having a classified board over the following treatment cohorts: 1999-2003, 2004-2008, 2009-2013, and 2014-2017. The regression is:

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

The dependent variable CB_{ijt} equals one if firm *i* for treatment cohort *j* in year *t* has a classified board, and zero otherwise. $Treat_{ij}$ equals one for the treatment firms that are added to the S&P 1500 Index, and zero otherwise. $Time_{tj}$ equals one for observations in period *t* relative to the treatment year for treatment cohort *j*, and zero otherwise. $Time_{jt-1}$ is the excluded base year. γ_{ij} are firm-treatment cohort fixed effects, and δ_{jt} are treatment cohort-year fixed effects. X_{ij} is the same set of firm-level variables as in Table 2 and are fixed at time *t*-1 for each treatment cohort *j*. $Post_{jt}$ equals one for the years *t* to *t*+3 after the treatment year for treatment cohort *j*, and zero otherwise. Variables are defined in Appendix A. 90% confidence intervals based on standard errors clustered by firm are reported.

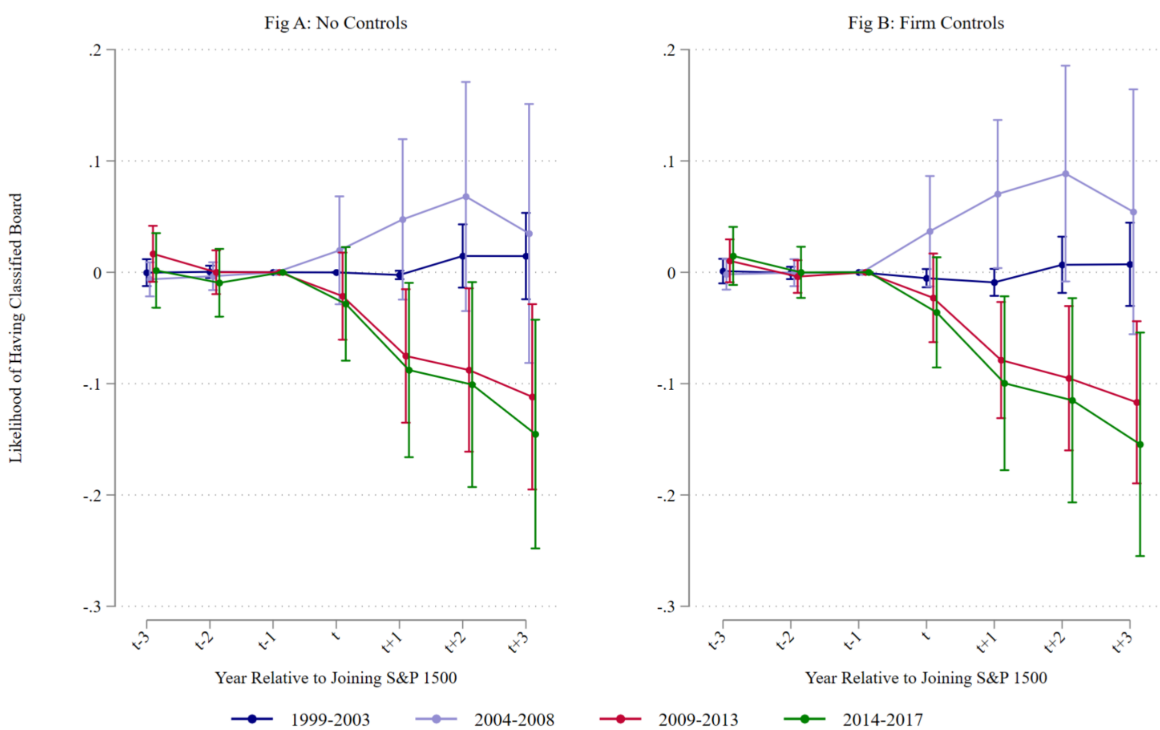

Figure 6
WSJ Articles and Academic Papers

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

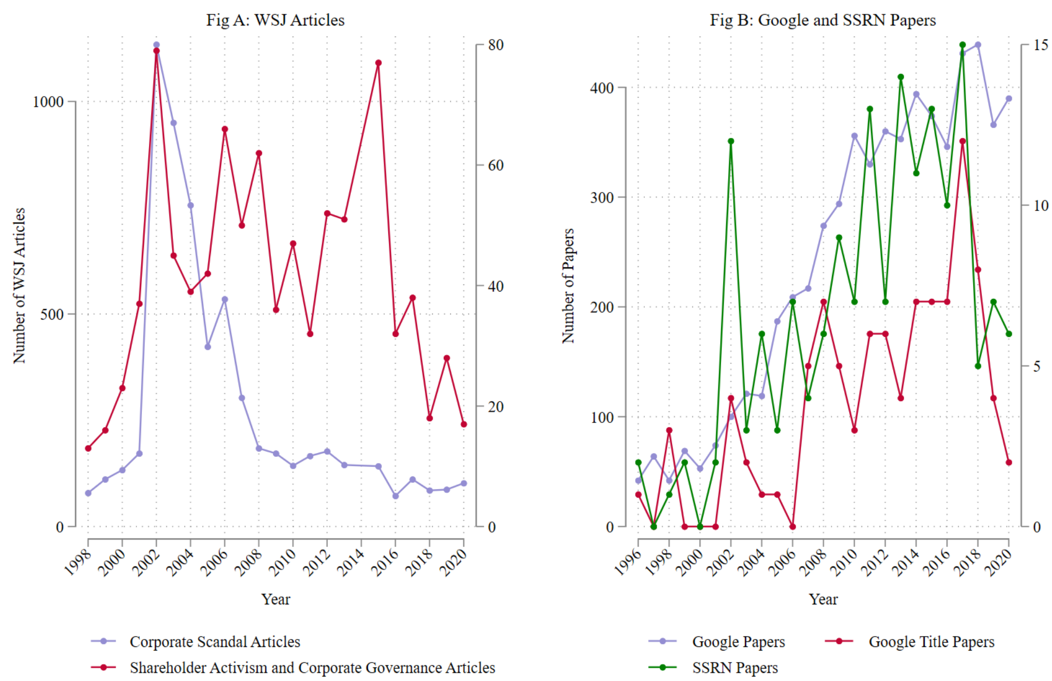

Figure 7
Institutional Ownership of S&P and Non-S&P 1500 Firms

Figure A plots the fraction of a firm's shares owned by institutional investors from 1996 to 2020. Figure B plots the fraction of a firm's shares owned by institutional investors labeled as quasi-indexers in Bushee (2001) and Bushee and Noe (2000) from 1996 to 2018. Figure C plots the fraction of a firm's shares owned by the Big Three institutional investors (Blackrock, State Street, Vanguard) from 1996 to 2020.

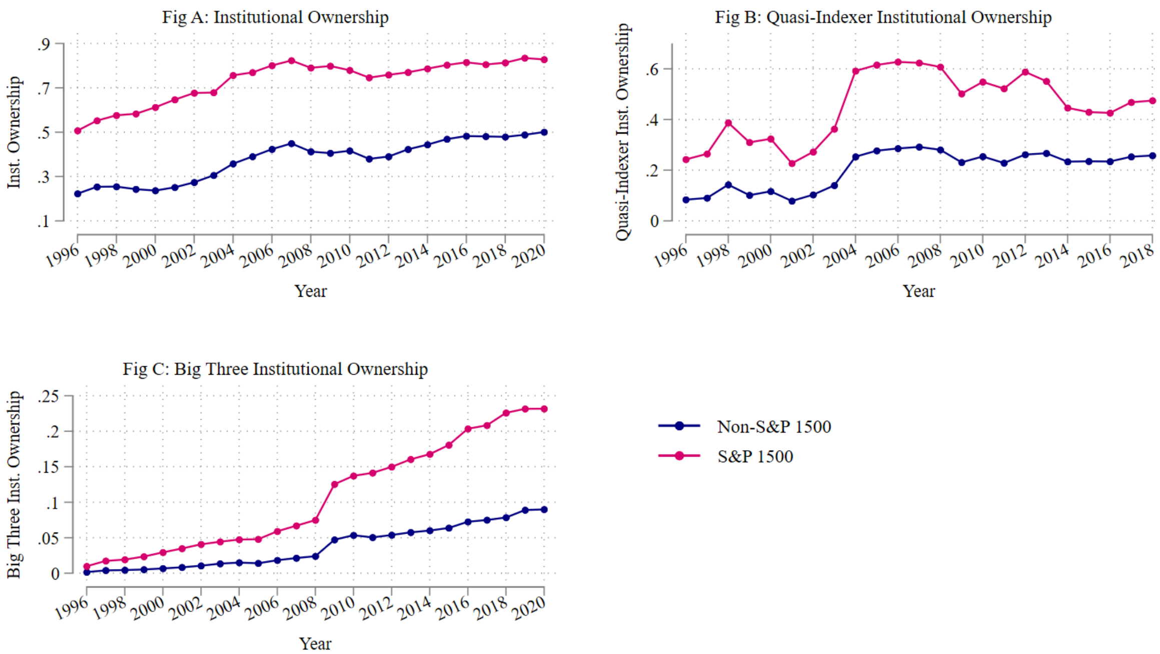

Figure 8
Relation between Institutional Ownership and Having a Classified Board

Figures A and B plot the coefficient estimates (β_{1996}-β_{2020} and ω_{1996}-ω_{2020}) from the following OLS regression examining the effect of institutional ownership on the likelihood of having a classified board (*CB*):

$$CB_{it} = \sum_{t=1996}^{2020} [\beta_t(IndexIO_{it} \times Year_t) + \omega_t(NonIndexIO_{it} \times Year_t)] + \Gamma X_{it} + \gamma_i + \delta_t \times \lambda_k + \varepsilon_{it}.$$

IndexIO equals the fraction of a firm's shares owned by index funds (quasi-indexers or the Big Three). *NonIndexIO* equals the fraction of a firm's shares owned by non-index institutional owners. *IndexIO* and *NonIndexIO* are normalized to have a standard deviation of one to ease comparisons. $Year_t$ equals one for observations in year *t*, and zero otherwise. X_{it} is the same set of firm-level variables as in Table 2. γ_i are firm fixed effects, and $\delta_t \times \lambda_k$ are two-digit SIC industry × year fixed effects. Figures C and E (D and F) plot the average predicted values of *CB* from the regressions in Figures A and B (after setting all values of index fund ownership to zero). Variables are defined in Appendix A. 90% confidence intervals based on standard errors clustered by firm are reported.

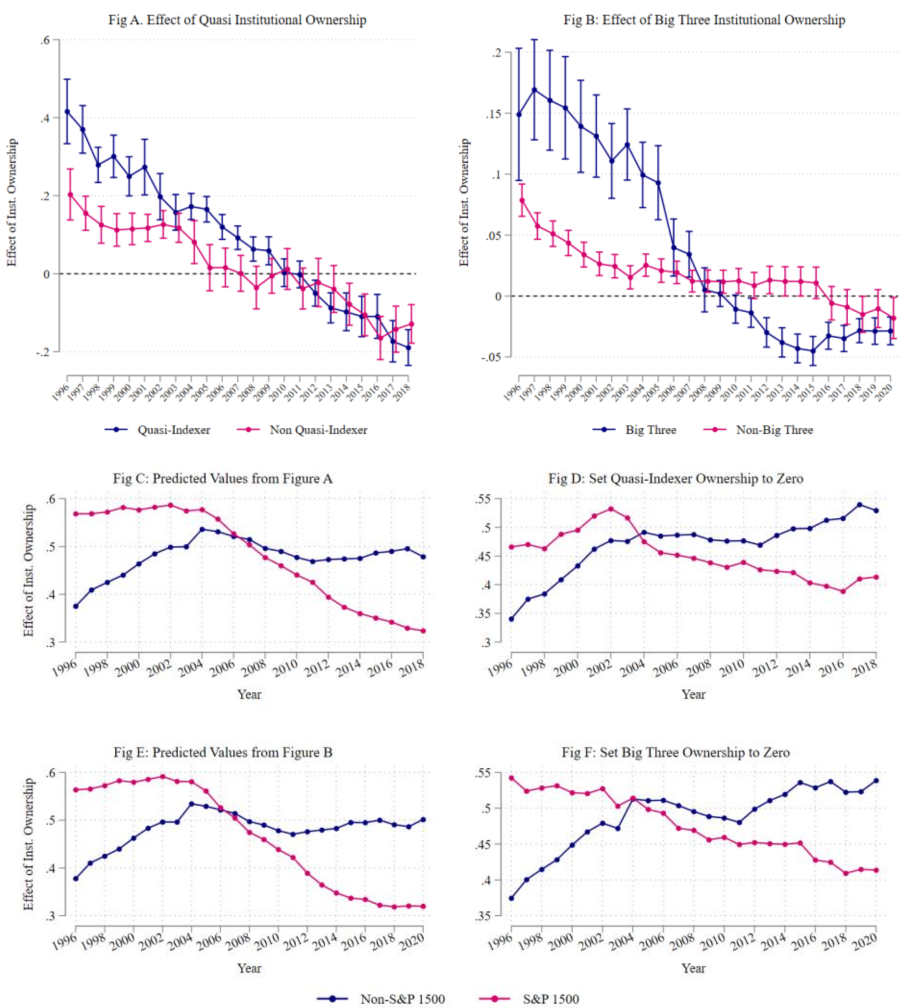

Figure 9
Fraction of Firms Receiving Proposals to Declassify

Figure A tabulates the fraction of firms receiving proposals to declassify their board for S&P 1500 and non-S&P 1500 firms over the period 2003 to 2020. Figure B breaks these rates into shareholder- and manager-sponsored proposals.

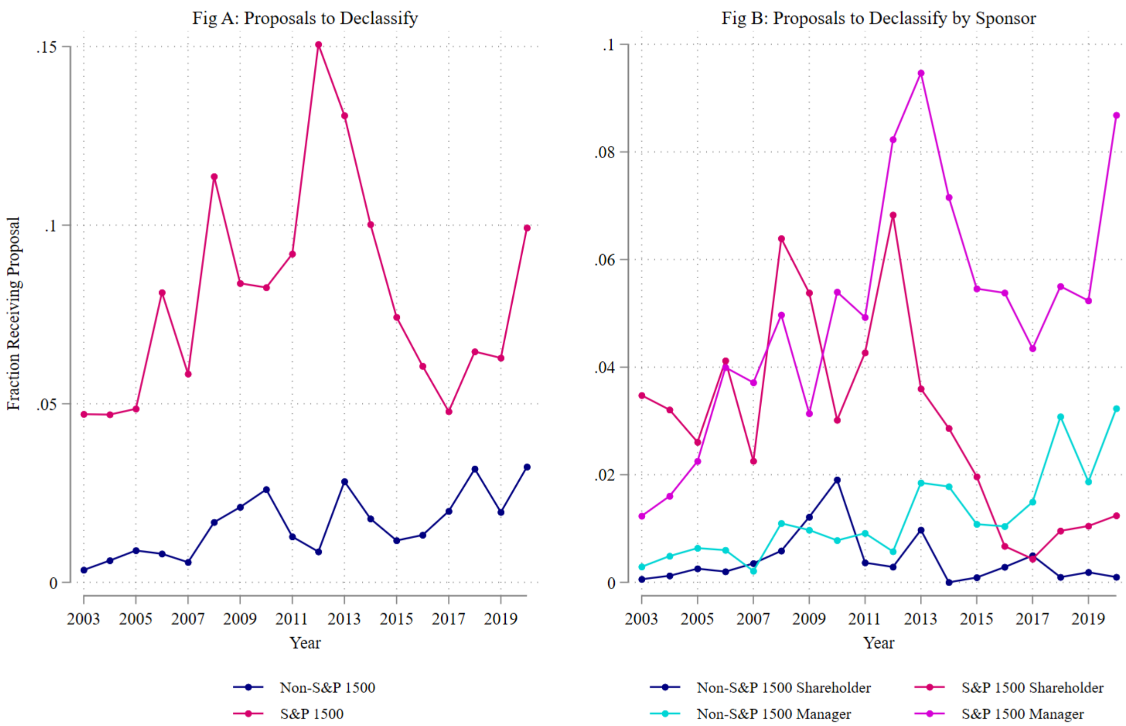

Figure 10
Pass Rates and Shareholder Support of Proposals to Declassify

Figure A tabulates the fraction of declassification proposals that received majority support and passed over time. Figure B breaks the pass rates into shareholder- and manager-sponsored proposals. Figure C plots the fraction of shares voted "for" declassifying a firm's board, and is further broken down by shareholder- and manager-sponsored proposals in Figure D. Figure E plots the fraction of mutual funds that voted "for" declassifying a firm's board, and is further broken down by shareholder- and manager-sponsored proposals in Figure F. The sample period is from 2003 to 2020 in Figures A-D and 2004 to 2020 in Figures E and F.

Figure 11
Fraction of Firms Targeted for a Takeover

This figure tabulates the fraction of firms targeted for a takeover over the sample period 1996 to 2020. 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. Figure A plots the average number of firms targeted for a takeover by year. Figure B adds controls for the same set of firm-level variables as in Table 2 and two-digit SIC industry fixed effects. Specifically, Figure B plots the coefficient estimates (β_{1996}-β_{2020} and ω_{1996}-ω_{2020}) from the following OLS regression of the targeted for takeover indicator (*Targeted*) on controls, where *SP* and *NonSP* are dummy variables indicating whether a firm is in the S&P 1500 Index or not:

$$Targeted_{it} = \sum_{t=1996}^{2020} (\beta_t Year_t \times SP_{it} + \omega_t Year_t \times NonSP_{it}) + \Gamma X_{it} + \lambda_k + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year t, and zero otherwise. X_{it} are firm-level characteristics, and λ_k are two-digit SIC industry fixed effects.

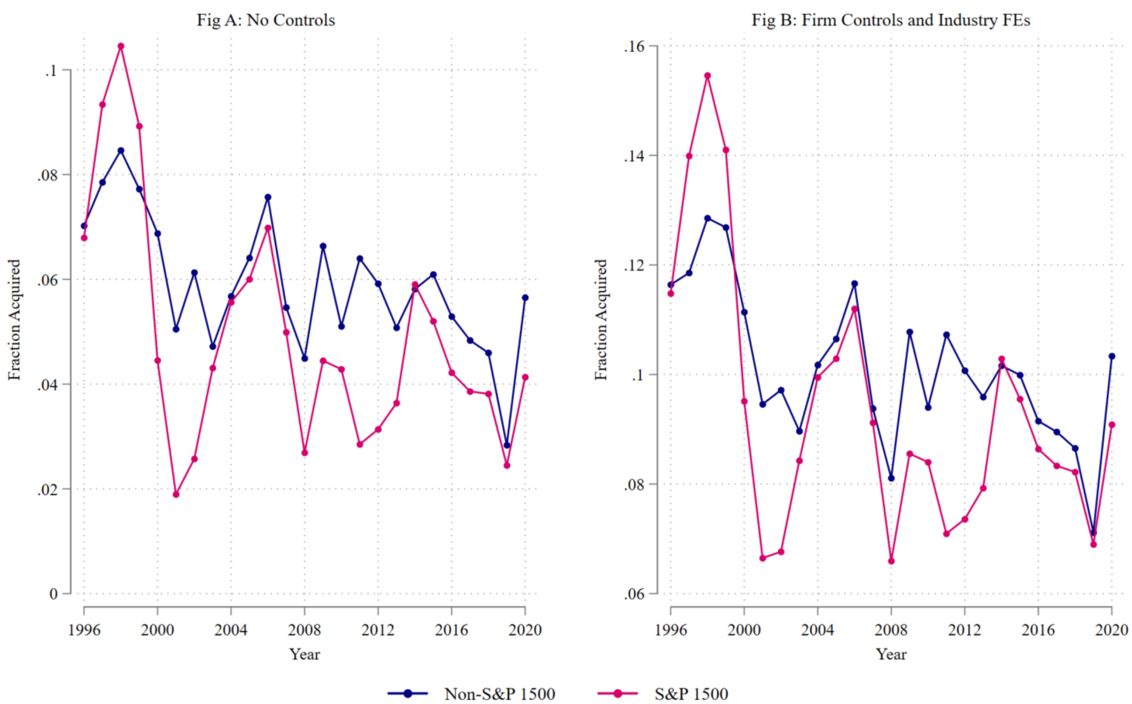

Table 1
Summary Statistics: S&P 1500 vs Non-S&P 1500 Firms

This table reports summary statistics for the main variables used in our analyses over the period 1996 to 2020. Variables are defined in Appendix A. *, **, and *** in the Mean and P50 columns for the S&P 1500 sample denote significance at the 10%, 5%, and 1% levels, respectively, for a test of whether the mean and median are different between the S&P 1500 and non-S&P 1500 samples. Standard errors are clustered by firm.

	S&P 1500 Sample (Obs = 33,472)			Non-S&P 1500 Sample (Obs = 64,667)		
	Mean	P50	Std Dev	Mean	P50	Std Dev
CB	0.467	0.000	0.499	0.479	0.000	0.500
MVE	9243.9***	2482.6***	17442.6	874.8	155.9	3505.8
Ln(MVE)	7.946***	7.817***	1.554	5.108	5.049	1.744
Assets	11514***	2700.4***	23003.1	1325.5	201.8	5490.0
Ln(Assets)	8.042***	7.901***	1.630	5.402	5.307	1.820
Age	26.15***	21.00***	19.38	11.98	8.000	11.33
Ln(Age)	3.026***	3.091***	0.793	2.204	2.197	0.874
Tobin's Q	1.953***	1.517***	1.334	2.026	1.343	1.801
OROA	0.127***	0.124***	0.099	-0.029	0.050	0.294
Lev	0.232***	0.219***	0.184	0.215	0.135	0.236
Capex	0.048***	0.034***	0.051	0.045	0.024	0.061
R&D	0.025***	0.000	0.053	0.075	0.000	0.151
Turn	1.968***	1.527***	1.556	1.432	0.825	1.765
Ln(Turn)	0.425***	0.423***	0.714	-0.229	-0.192	1.124
Volatility	0.106***	0.091***	0.062	0.168	0.142	0.108
IO	0.737***	0.777***	0.210	0.370	0.308	0.300
Numest	10.97***	9.364***	7.372	3.232	1.833	4.192
Ln(Numest)	2.262***	2.338***	0.715	1.060	1.041	0.862
Delaware	0.591***	1.000	0.492	0.571	1.000	0.495

Table 2
Determinants of Classified Boards

This table reports the results from OLS regressions relating classified board status to firm characteristics between 1996 and 2020. The dependent variable *CB* in columns 1-2 and 4-5 equals one if a firm has a classified board in year *t*, and zero otherwise. Columns 3 and 6 report results testing whether the coefficients in columns 1-2 and 4-5 are different, respectively. Variables are defined in Appendix A. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	S&P 1500 Sample	Non-S&P 1500 Sample	Difference	S&P 1500 Sample	Non-S&P 1500 Sample	Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Ln(Assets)	-0.054***	0.035***	-0.088***	0.013	0.013***	0.000
	(-7.67)	(7.47)	(-10.92)	(1.22)	(2.78)	(0.04)
Ln(Age)	-0.076***	-0.063***	-0.014	0.004	0.006	-0.002
	(-7.25)	(-10.11)	(-1.18)	(0.24)	(0.79)	(-0.12)
Tobin's Q	-0.024***	-0.009***	-0.015**	0.009**	-0.000	0.009**
	(-4.26)	(-3.64)	(-2.49)	(2.42)	(-0.22)	(2.41)
OROA	0.091	-0.039*	0.130*	-0.059	-0.024**	-0.036
	(1.25)	(-1.93)	(1.74)	(-1.41)	(-2.37)	(-0.83)
Lev	0.007	-0.102***	0.109**	0.041	0.027**	0.014
	(0.18)	(-4.72)	(2.50)	(1.28)	(2.19)	(0.42)
Capex	0.221	-0.243***	0.465***	0.167*	0.012	0.155*
	(1.44)	(-3.18)	(2.87)	(1.94)	(0.43)	(1.72)
R&D	-0.158	0.197***	-0.355**	0.008	0.030	-0.022
	(-0.94)	(4.40)	(-2.08)	(0.07)	(1.58)	(-0.19)
Ln(Turn)	-0.092***	-0.024***	-0.068***	-0.007	0.008***	-0.015*
	(-8.65)	(-4.88)	(-5.92)	(-0.84)	(3.49)	(-1.69)
Volatility	0.056	-0.119***	0.176*	-0.030	-0.005	-0.025
	(0.66)	(-3.74)	(1.94)	(-0.66)	(-0.41)	(-0.53)
IO	-0.017	0.078***	-0.095**	0.059***	-0.013	0.072***
	(-0.49)	(3.52)	(-2.42)	(2.63)	(-1.08)	(2.86)
Ln(Numest)	0.032**	0.029***	0.002	0.013	0.006	0.007
	(2.16)	(3.55)	(0.15)	(1.29)	(1.55)	(0.62)
Delaware	-0.014	0.031**	-0.045**	-0.005	0.044**	-0.049
	(-0.77)	(2.48)	(-2.16)	(-0.16)	(2.33)	(-1.32)
SIC2×Year FE				✓	✓	
Firm FE				✓	✓	
Observations	33,472	64,667		33,081	62,679	
Adj R^2	0.060	0.049		0.794	0.897	

Table 3
Classified Boards and M&A CARs

This table reports the results from OLS regressions relating M&A announcement CARs to classified board status. The dependent variable *CAR*(*-2,+2*) is the five-day bidder cumulative abnormal return around a deal announcement. *CB* equals one if a firm has a classified board in year *t*, and zero otherwise. In columns 1-3, the sample periods are 1990-2003, 1996-2003, and 1996-2020, respectively, and *CB* is based on data from the ISS governance database. In columns 4 and 5, the sample period is from 1996 to 2020, and *CB* is based on our new dataset. Variables are defined in Appendix A. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	ISS Sample			S&P 1500 Sample	Non-S&P 1500 Sample
	(1)	(2)	(3)	(4)	(5)
CB	-0.431**	-0.411	-0.010	-0.049	-0.433**
	(-2.18)	(-1.64)	(-0.07)	(-0.32)	(-2.06)
Ln(Assets)	-0.297***	-0.317***	-0.268***	-0.290***	-0.363***
	(-4.67)	(-4.17)	(-3.18)	(-3.36)	(-3.31)
Tobin's Q	-0.055	-0.043	0.087	0.029	-0.134
	(-0.74)	(-0.54)	(1.13)	(0.35)	(-1.61)
OROA	-0.462	-0.467	-1.774	0.120	0.263
	(-0.33)	(-0.28)	(-1.37)	(0.09)	(0.27)
Lev	0.646	0.734	1.422***	1.648***	1.445**
	(0.95)	(0.86)	(2.59)	(2.87)	(2.31)
Relative Size	0.850	0.322	1.028**	0.924*	3.797***
	(1.49)	(0.46)	(2.12)	(1.81)	(10.18)
Tech	0.717**	0.757*	0.531**	0.565**	-0.006
	(2.21)	(1.95)	(2.12)	(2.23)	(-0.02)
Relative Size×Tech	-7.889***	-8.065***	-3.906***	-3.592***	-2.526**
	(-4.62)	(-4.06)	(-3.07)	(-2.86)	(-2.36)
Public Target	-2.191***	-2.136***	-1.962***	-2.140***	-3.923***
	(-7.80)	(-5.89)	(-7.94)	(-8.57)	(-10.66)
Private Target	-0.414*	-0.602*	-0.492***	-0.611***	-0.529**
	(-1.68)	(-1.92)	(-2.86)	(-3.50)	(-2.26)
All Cash	0.189	0.178	0.242	0.321**	0.440*
	(0.85)	(0.63)	(1.53)	(1.98)	(1.89)
Stock Deal	-0.265	-0.392	-0.510**	-0.390	0.431
	(-1.00)	(-1.15)	(-2.02)	(-1.54)	(1.62)
Diversify	-0.313*	-0.154	-0.230	-0.144	-0.149
	(-1.68)	(-0.64)	(-1.40)	(-0.90)	(-0.65)
Runup	0.362	0.372	0.078	0.003	0.403**
	(1.09)	(1.00)	(0.29)	(0.01)	(1.99)
Tender	1.243***	1.228**	0.760**	1.005***	2.362**
	(2.77)	(2.24)	(2.02)	(2.75)	(2.54)
IO			-0.445	-0.364	-1.164**
			(-0.95)	(-0.75)	(-2.51)
Ln(Numest)			-0.385**	-0.305	-0.081
			(-2.14)	(-1.62)	(-0.42)
Ln(Age)			0.063	0.057	0.085
			(0.53)	(0.49)	(0.69)
Year FE	✓	✓	✓	✓	✓
SIC2 FE			✓	✓	✓
Observations	5,312	3,701	8,992	8,639	9,672
Adj R^2	0.042	0.038	0.037	0.037	0.064

Table 4
Classified Boards and Earnings Management

This table reports the results from OLS regressions relating earnings management to classified board status. The dependent variable earnings management (*EM*) is the performance matched absolute value of discretionary accruals. *CB* equals one if a firm has a classified board in year *t*, and zero otherwise. In columns 1 and 2, the sample periods are from 1995-2001 and 1996-2020, respectively, and *CB* is based on data from the ISS governance database. In columns 3 and 4, the sample period is from 1996 to 2020, and *CB* is based on our new dataset. Variables are defined in Appendix A. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	ISS Sample		S&P 1500 Sample	Non-S&P 1500 Sample
	(1)	(2)	(3)	(4)
CB	-0.005**	-0.003***	-0.004***	-0.002
	(-2.12)	(-2.86)	(-3.37)	(-1.51)
Tobin's Q	0.007***	0.006***	0.006***	0.006***
	(5.78)	(8.99)	(9.17)	(10.80)
Abs(ΔOROA)	0.124***	0.156***	0.155***	0.139***
	(5.24)	(10.68)	(9.89)	(21.65)
Negative OROA	0.017**	0.013***	0.010***	0.018***
	(2.15)	(4.03)	(2.65)	(10.86)
Lev	-0.022***	-0.007**	-0.016***	0.008**
	(-2.85)	(-1.96)	(-3.99)	(2.37)
Ln(Assets)	-0.007***	-0.005***	-0.001**	-0.003***
	(-7.47)	(-9.94)	(-2.17)	(-4.66)
Delaware	0.010***	0.005***	0.003**	-0.002
	(4.06)	(4.33)	(2.36)	(-1.15)
IO			0.003	-0.019***
			(0.99)	(-6.67)
Ln(Numest)			-0.004***	-0.004***
			(-3.52)	(-3.17)
Ln(Age)			-0.007***	-0.006***
			(-7.78)	(-6.39)
Year FE	✓	✓	✓	✓
Observations	7,619	29,924	27,532	44,838
Adj R^2	0.053	0.055	0.054	0.097

Table 5
Classified Boards and Tobin's Q

This table reports the results from OLS regressions relating firm value to classified board status. The dependent variable *Tobin's Q* is market value of assets scaled by book value of assets. *CB* equals one if a firm has a classified board in year *t*, and zero otherwise. In columns 1 and 2, the sample period is from 1995 to 2002 and 1996 to 2020, respectively, and *CB* is based on data from the ISS governance database. In columns 3-6, the sample period is from 1996 to 2020, and *CB* is based on our new dataset. Variables are defined in Appendix A. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	ISS Sample		S&P 1500 Sample	Non-S&P 1500 Sample	S&P 1500 Sample	Non-S&P 1500 Sample
	(1)	(2)	(3)	(4)	(5)	(6)
CB	-0.109**	-0.071***	-0.081***	-0.112***	0.090**	-0.024
	(-2.42)	(-2.83)	(-3.04)	(-4.51)	(2.30)	(-0.47)
Delaware	0.031	0.033	0.035	-0.005	-0.046	-0.105
	(0.65)	(1.15)	(1.21)	(-0.20)	(-0.59)	(-1.34)
Capex	2.199***	0.561*	0.342	1.283***	1.550***	1.125***
	(4.50)	(1.72)	(0.90)	(6.35)	(4.70)	(5.72)
Lev	-0.935***	-0.196**	-0.339***	0.050	-0.187	0.137*
	(-5.28)	(-2.02)	(-2.91)	(0.82)	(-1.62)	(1.81)
Ln(Assets)	0.000	-0.223***	-0.209***	-0.306***	-0.458***	-0.519***
	(0.02)	(-14.98)	(-12.93)	(-23.66)	(-12.78)	(-20.98)
OROA	3.183***	4.796***	6.011***	-0.370***	4.362***	0.551***
	(6.54)	(16.76)	(16.30)	(-3.92)	(12.98)	(6.33)
R&D		8.351***	8.487***	2.766***	4.696***	2.417***
		(20.92)	(16.04)	(15.66)	(5.63)	(11.84)
Ln(Age)		-0.020	-0.016	-0.070***	-0.090**	-0.233***
		(-1.12)	(-0.87)	(-4.75)	(-2.30)	(-6.95)
Ln(Turn)		-0.067***	-0.048*	0.054***	0.035	0.130***
		(-2.88)	(-1.85)	(4.01)	(1.30)	(9.26)
Volatility		-0.124	0.178	0.925***	0.372**	1.097***
		(-0.63)	(0.82)	(8.12)	(2.14)	(11.12)
IO		-0.248***	-0.238***	0.867***	0.276***	1.321***
		(-4.01)	(-3.49)	(15.87)	(4.87)	(20.31)
Ln(Numest)		0.508***	0.490***	0.408***	0.248***	0.137***
		(19.24)	(16.26)	(19.72)	(7.31)	(6.79)
Year FE	✓					
SIC2 FE	✓					
SIC2×Year FE		✓	✓	✓	✓	✓
Firm FE					✓	✓
Observations	10,610	36,313	33,403	64,563	33,081	62,682
Adj R^2	0.260	0.421	0.455	0.320	0.708	0.612

Classified Boards: Endangered Species or Hiding in Plain Sight?

Internet Appendix

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IA.1. Predicting Classified Board Status

IA.1.1. Sample selection

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

Table IA.1
Sample Selection

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

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

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

A concern is that regular expressions cannot capture all potential variants of "election of directors" mentioned in DEF 14As because language is dynamic and not all firms follow the same disclosure format. Thus, our second step is to conduct two specific keyword searches that would indicate the presence of a classified board. First, we search the DEF 14A filings for variations of the word "class" and then keep the ten words before and after each instance the keyword is found. We require the word "director" or "board" to appear within these ten words for us to consider it a valid keyword match. This restriction is intended to remove instances where "class" refers to share classes. Next, we search the DEF 14A filings for variations of the word "term" and then keep the ten words before and after each instance the keyword is found. We require the word “director” or “board”, as well as the phrase “[number] [optional non-word character] year” or “stagger”, to appear within these ten words for us to consider it a valid keyword match. This last criterion is designed to capture instances when a firm mentions directors having “three-year terms” and other variations of this phrasing. We identify at least one of these keywords for 66.0% of the sample. These keywords are found in 59.1% of the sample that we could not identify the election of directors paragraphs described earlier. We then combine all the paragraphs and texts into one corpus for each CIK-FDATE pair observation.[17]

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

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

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

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

IA.1.2. Text processing and machine learning

After we obtain our sample of DEF 14A filings, our fourth step is to remove from the text the same set of stop words (except "i") used in Frankel, Jennings, and Lee (2021) and numbers with more than one digit because these numbers are unrelated to classified boards and more likely to capture years, page numbers, and director ages. We further reduce each word to its stem using the Porter stemmer technique so that, for example, "elects", "elected", "election", and "electing" all become "elect". We then convert this text into unigrams and bigrams (one- and two-word phrases) that indicate whether the specific phrase appears at least once. We only include one- and two-word phrases that appear in at least 1,000 of the 110,511 observations, resulting in a corpus of 2,287 variables that we use as inputs into the RF Classifier algorithm. After we obtain all the related text, we merge it with the ISS database for which we know the classified board status of firms. We have 39,998 DEF 14A filings matched to ISS. Among these observations, we use 80% of them as a training sample and the remaining 20% as an out-of-sample test dataset.

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

We seed the training sample with the following parameters: the number of trees in the forest (starting from 10 to 1,000, with 110 as the interval), the maximum number of levels in each tree (starting from 10 to 110, with 10 as the interval), the minimum number of samples required to split a node (2, 5, 10, 15, 20, 25), and the minimum number of samples required at each leaf node (1, 2, 4, 8, 16, 32, 64). The maximum number of predictors is either the square root of all predictors or the logarithm base 2 of the number of predictors. The RF Classifier algorithm runs through all combinations of these parameters and then determines the best parameters given the best accuracy using cross-validation techniques in the training sample. The results from our simulations indicate the optimal number of trees in the forest is 780, and we require at least two samples to split a node and a minimum of one observation on each leaf node. The optimal number of levels in each tree is determined by each individual tree.[18] The optimal number of predictors we use for each tree is the logarithm of the total number of predictors to the base 2.[19] We then use the "best RF" to predict the classified board status for the out-of-sample test dataset and evaluate the algorithm's success. We then extend the predictions to the universe of firms with DEF 14A filings.

IA.1.3. Validating our classified board predictions and finalizing the dataset

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

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

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[18] The average level of depth in our testing sample is 84, and the minimum (maximum) level of depth is 54 (129).
[19] In untabulated results, we follow Frankel et al. (2021) and use 5,000 trees. The model gives almost identical out-of-sample error rates, suggesting that our optimal parameters are sufficient to determine a firm's classified board status.

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

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

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

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

IA.2. Additional Results

Figure IA.2.1
Fraction of Firms with Classified Boards: Controlling for Firm Age

Figures A-D tabulate the fraction of firms with a classified board by year, split between S&P and non-S&P 1500 firms. Figures A, C, and D control for the same set of firm-level variables as in Table 2, firm fixed effects, and firm age fixed effects. Figure B first matches S&P 1500 to non-S&P 1500 firms by estimating a propensity score based on the same firm-level characteristics as in Table 2 (except firm age) and further matching exactly on two-digit SIC industry, year, and firm age. Figures C and D further restrict the sample to firms that have been public for at least five and ten years, respectively.

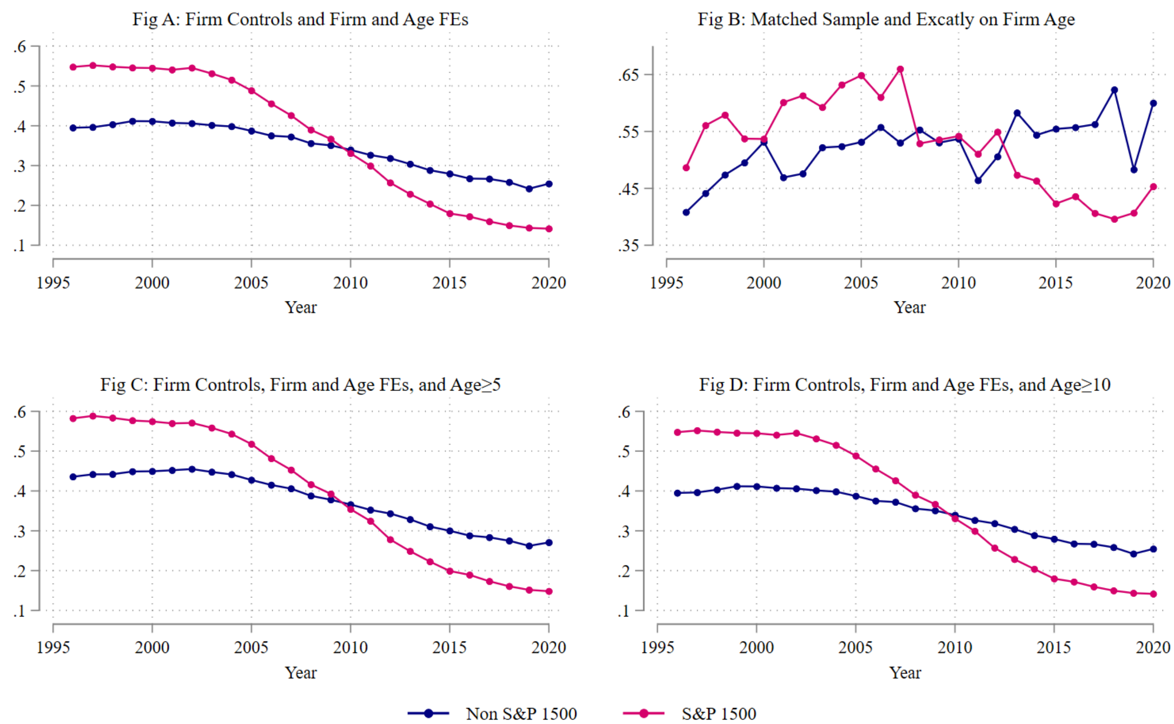

Figure IA.2.2
Fraction of Firms Adopting Classified Boards

Figures A and B tabulate the fraction of firms adopting a classified board by year. Figure C controls for the same set of firm-level variables as in Table 2. Figure D adds firm fixed effects. Figure E controls for firm fixed effects and quadratic terms of the controls in Figure C. Figures C-E plot the coefficient estimates (β_{1996}-β_{2020} and ω_{1996}-ω_{2020}) from their respective versions of following the OLS regression of an indicator variable equal to one if a firm adopts a classified board in year *t* (*Adopt*) on controls, where *SP* and *NonSP* are dummy variables indicating whether a firm is in the S&P 1500 Index or not:

$$Adopt_{it} = \sum_{t=1996}^{2020} (\beta_t Year_t \times SP_{it} + \omega_t Year_t \times NonSP_{it}) + \Gamma X_{it} + \gamma_i + \varepsilon_{it}.$$

$Year_t$ equals one for observations in year *t*, and zero otherwise. X_{it} are firm-level characteristics, and γ_i are firm fixed effects. Figure F first matches S&P 1500 to non-S&P 1500 firms by estimating a propensity score based on the same firm-level characteristics as in Figure C and further matching exactly on two-digit SIC industry and year.

Table IA.2
Determinants of Board Declassification

This table reports the results from OLS regressions relating the likelihood of declassifying a board to firm characteristics between 1996 and 2020. The dependent variable *Declassify* in columns 1-2 and 4-5 equals one if a firm has a classified board in year *t* and not a classified board in year *t*+1, and zero otherwise. To enter the sample, a firm must have a classified board in year *t*. Columns 3 and 6 report results testing whether the coefficients in columns 1-2 and 4-5 are different, respectively. Variables are defined in Appendix A. *t*-statistics in parentheses are calculated from standard errors clustered by firm. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	S&P 1500 Sample (1)	Non-S&P 1500 Sample (2)	Difference (3)	S&P 1500 Sample (4)	Non-S&P 1500 Sample (5)	Difference (6)
Ln(Assets)	0.017***	0.002***	0.014***	0.017***	-0.003	0.020***
	(10.71)	(3.93)	(8.53)	(2.88)	(-1.41)	(3.20)
Ln(Age)	0.003	0.001*	0.001	-0.012	0.001	-0.013
	(1.48)	(1.65)	(0.67)	(-0.93)	(0.29)	(-0.99)
Tobin's Q	0.000	-0.001*	0.001	-0.004**	-0.001	-0.004*
	(0.41)	(-1.87)	(0.89)	(-2.26)	(-1.53)	(-1.87)
OROA	-0.015	-0.005	-0.010	-0.012	0.002	-0.014
	(-0.94)	(-1.62)	(-0.62)	(-0.44)	(0.35)	(-0.51)
Lev	-0.030***	0.001	-0.031***	-0.021	-0.004	-0.017
	(-3.52)	(0.43)	(-3.48)	(-1.14)	(-0.64)	(-0.91)
Capex	-0.028	-0.013	-0.015	-0.007	0.008	-0.016
	(-1.18)	(-1.22)	(-0.58)	(-0.12)	(0.49)	(-0.26)
R&D	-0.014	-0.007	-0.007	0.091	-0.010	0.101
	(-0.55)	(-1.24)	(-0.27)	(1.35)	(-1.08)	(1.51)
Ln(Turn)	0.017***	0.003***	0.013***	-0.004	0.000	-0.004
	(6.81)	(3.90)	(5.20)	(-0.66)	(0.41)	(-0.74)
Volatility	-0.087***	-0.009	-0.078***	0.043	0.002	0.042
	(-3.37)	(-1.14)	(-2.90)	(1.12)	(0.19)	(1.06)
IO	0.002	0.003	-0.001	-0.014	0.002	-0.016
	(0.21)	(0.84)	(-0.11)	(-0.82)	(0.40)	(-0.91)
Ln(Numest)	-0.005**	-0.003***	-0.002	-0.015***	-0.002	-0.014**
	(-1.99)	(-2.60)	(-0.67)	(-2.69)	(-0.78)	(-2.26)
Delaware	-0.002	-0.002*	0.000	-0.014	-0.013*	-0.001
	(-0.69)	(-1.69)	(0.16)	(-0.81)	(-1.74)	(-0.05)
SIC2×Year FE				✓	✓	
Firm FE				✓	✓	
Observations	15,687	30,953		15,301	29,734	
Adj R^2	0.021	0.002		0.083	0.104	