A Diverse View on Board Diversity☆

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Abstract

Boards of U.S. public firms have shown progress in demographic diversity, but little progress in diversity of experience, skill, institutions, and viewpoints (proxied by political stance). The addition of directors who contribute to demographic diversity also contributes positively to experience and skill diversity, but has an asymmetric effect on viewpoint diversity. The addition of demographically diverse directors is associated with an increase (decrease) in political stance diversity among boards that were dominated by directors leaning Republican (Democratic), resulting in "bluer" boards for both groups. The asymmetric effect on viewpoint diversity cannot be explained by the availability of candidates of varying political stances. Finally, experience and skill diversity emerge as the most critical factors of boards in guiding firms through the unforeseen COVID-19 crisis.

Keywords: Board Diversity; Demographic diversity; Viewpoint diversity; Polarization; Crisis Management.

1. Introduction

At the heart of corporate governance lies the board of directors, a relatively small group of professionals entrusted with the responsibility of shaping an organization's strategic course and overseeing its operations. The past two decades have witnessed a notable surge in a subbranch of governance research concerning board diversity, mirroring a contemporary discourse extending to many areas in economics research to encompass broader issues related to diversity and inclusion. Most published academic studies conclude that there are positive effects of board diversity, supported by logical reasoning or empirical evidence. The potential benefits of board diversity are manifold, including both economic advantages, such as enhanced firm performance, and social benefits that contribute to a more harmonious society. The two dimensions are not mutually exclusive and are often intertwined.

From economic standpoint, a diverse board amalgamates a wide range of perspectives, experiences, and expertise, which can produce more comprehensive and nuanced decision-making processes. Different backgrounds and viewpoints can question established thoughts, encourage innovative solutions, and facilitate the unveiling of unnoticed gaps. On the societal front, board diversity constitutes a stride toward rectifying historical imbalances in the representation of various groups, fostering a society in which a maximal number of individuals perceive a vested interest and ready role models for success. The two sides are also not mutually exclusive. A board that mirrors the diversity of the stakeholders that businesses engage with is arguably better poised to comprehend and respond to the latter's needs and preferences, cultivating business opportunities as well as bolstering alignment and trust, e.g., in attracting a diverse pool of talents.

Therefore, the concept of "board diversity" itself is inherently diverse, encapsulating facets ranging from demographics (e.g., gender, race, and ethnicity) to professional backgrounds (e.g., work experience, industry expertise, and skill sets), as well as viewpoints on the world and businesses (e.g., social values and political stances). Despite this high-dimensional nature of board diversity, the literature has focused predominantly on gender (Adams and Ferreira, 2009; Ahern and Dittmar, 2012; Kim and Starks, 2016; Griffin et al., 2021; Eckbo et al., 2022; Gormley et al., 2023b; Jiang, 2023; Giannetti and Wang, 2023; Bian et al., 2023; Cziraki and Robertson, 2023) and race/ethnicity (Field et al., 2020). This focus is understandable, not only because the demographics are identifiable markers that could be monitored and measured, but also because of organizations' commitments to rectify historical and ongoing disparities. Some recent research has expanded diversity to more dimensions, including education background and experience (e.g., Bernile et al., 2018; Cai et al., 2022) and skill sets (e.g., Adams et al., 2018) of board directors.

There is merit in exploring a more diverse view of board diversity, acknowledging that each dimension represents a fragment of the mosaic that contributes to a diverse and high-performing board. This is the purpose of our study: We assess the complementarity and trade-offs among dimensions of diversity in terms of demographics (gender, race/ethnicity), experience, skills, and viewpoints (as proxied by age and political stance), based on the evolution and current states of board diversity in multiple dimensions. Aiming at this goal, we start with constructing a comprehensive database of directors and boards of U.S. public firms from 2000 to 2021 by merging three databases (BoardEx and the ISS Board database, both from WRDS; and BoardEdge from Equilar) and by completing the missing information in covered firms with additional data directly scripted from proxy statements. The resulting sample, covering 5,453 unique firms and 52,284 unique directors, including the 36,286 directors who entered the database during the sample period, represents the most comprehensive and granular database of board directors that has been used in empirical research.

The key inputs to our study involve a series of constructed board diversity measures, which are normalized to be variables bounded between 0 (no diversity) and 1 (perfect diversity). The first aspect of diversity that we consider is demographic diversity. Gender diversity is quantified by the proportion of female directors on a board. Racial diversity is measured as one minus the Herfindahl index over the four major racial/ethnic groups: AAPI, Black, Hispanic, and White. Demographic information is collected using a combination of methods. Although the combined data set provides gender information for all directors and race/ethnicity information for 59% of them, the coverage serves as a training dataset to apply an ensemble of algorithms to classify the remaining directors. Integral training and estimation samples, more granular input, and ensemble methods produce superior precision and recall rates compared to algorithmic racial and ethnic classification reported in recent studies. Consequently, we can present a more comprehensive and accurate assessment of the demographic diversity of U.S. public corporate boards than previously attempted.

The second group of diversity indicators captures the degree to which a board consists of directors with a variety of experience and skills. The first measure in this group, experience diversity, is measured as one minus the average pairwise similarity of director resumes, calculated using natural language processing (NLP) tools. The second measure, skill diversity, is constructed analogously using a skill vector for each director parsed from bios. The vector consists of the following five skill elements: Leadership, Law, Regulation/Government, Marketing, Finance/Accounting, Operation, Technology, and Academic.

The last group of diversity measures capture individual viewpoints, which have been the least studied in the literature and also the most difficult to measure. We resort to two proxies. The first is age, based on voluminous studies in the social sciences showing that each age cohort has its distinct average view points due to both the place of individuals in the life cycle and a common macro social-economic exposure, which impacts business decisions (Malmendier and Nagel, 2011, 2015). The second proxy for viewpoints is partisan affiliation, classified based on political contributions to federally registered political committees tracked by the Federal Election Commission (FEC). A large body of research in political and social science and surveys show distinct partisan lines in terms of life, social, and business values (e.g., Iyengar et al., 2012; Mason, 2015; Boxell et al., 2023; Howard et al., 2022). Importantly, recent studies show that political stance is correlated with business operations or decisions (e.g., Bertrand et al., 2018; Duchin et al., 2019; Gormley et al., 2021; Kempf and Tsoutsoura, 2021; Dagostino et al., 2023; Gormley et al., 2023a), a context most relevant to the purpose of our research. For example, Bertrand et al. (2018) show that politically skewed leadership leads to distortions in corporate decisions and that these distortions are not offset by other benefits.

With the constructed data in hand, we start by documenting the general trends in diversity measures. During the first two decades of the millennium, U.S. public firm boards have made remarkable progress in demographic diversity in terms of representation of female and racial minority directors. However, experience and skill diversity have been declining, suggesting that directors, regardless of their demographics, tend to be drawn from increasingly similar social-economic backgrounds. Finally, age diversity experienced a U-turn, and diversity of political views has been stable during the sample period. Given the focus on board diversity in terms of gender and race, evident from the Californian gender quota law in 2018, the Nasdaq board diversity rules[1], and the "Big Three" board gender diversity campaign in 2017, we are curious to discover that new directors who are

[1]According to the rule, Nasdaq-listed issuers' boards will be expected to (i.e., "comply or explain") have at least one director who: (1) Self-identifies as female; or (2) Self-identifies as an underrepresented minority or as LGBTQ+ in 2022; and the quota will increase to at least two diverse directors, including one from each diversity group starting from 2025.

gender or racial diverse also contribute to incremental board diversity in terms of skills and experience, although the effect on viewpoints is more mixed. The effect is particularly strong for female and Black directors. Therefore, it is generally encouraging that diversities along most dimensions do not face trade-offs.

Given the rising political polarization of corporate America (Autor, Dorn, Hanson and Majlesi, 2020; Fos, Kempf and Tsoutsoura, 2023), we further divide the sample into boards (at the firm-year level) dominated by Republican or Democratic leaning directors. Here, an interesting division arises. In both types of boards, gender/racial minority directors contribute positively to experience and skill diversity, but their impacts on a board's political stance diversity are opposite to each other. Republic-majority boards appoint new minority directors who are more likely to be from the opposite political spectrum, while Democratic-majority boards appoint new minority directors who are more likely to hold similar political views. Therefore, as corporate boards become more gender and racially diverse, we expect conservative leaning boards to become more balanced, but progressive leaning boards to become more homogeneous over time. As such, all corporate boards are evolving in the progressive direction while becoming more diverse demographically. Such a contrast and trend could not have been inferred from the aggregate sample that pools the two types of board together and have not been noted in either research or commentaries.

The opposite evolution of political diversity between the two groups of boards involves the appointment of progressive leaning minority directors. Thus, it could be argued that corporate boards merely accommodate the supply of female and minority candidates, who are perceived to be majority progressive leaning.[2] We would like to

[2]While individual viewpoints and voting behavior can vary widely and cannot be identified accurately, both public opinion surveys and elective exit polls consistently predict that women and racial minorities vote more often for Democratic candidates. However, because director candidates tend to be older (more Republican leaning), more educated (more Democratic leaning), higher earning (nonmonotonic) and more business-oriented than the general population, presumptions in either direction cannot be justified for the

emphasize that neglecting individual differences and relying solely on group-level statistics is contrary to the mission of the diversity movement, which calls for institutions to address perceived limitations in the pipelines in order to achieve greater diversity. Furthermore, we conducted two tests testing the null hypothesis that candidate supply drives the result of the asymmetric inclusion of political views.

In the first test, we show that Democratic-leaning firms in "red" states (based on the most recent Presidential election) are not more likely to recruit minority directors who are from the other side of political stances than those in "blue" states, although the supply of such candidates for the first group of firms should be less of an issue. On the other hand, Republic-leaning firms in "red" states still recruit "blue" minority directors, i.e., those who do not share the dominant political view of either the current board members or the residing state. One could still argue that the political views of the general population in red and blue states may not be an accuracy proxy for the supply of talents that could qualify as directors of corporate boards, as they are not representative of the population in terms of age, education, income, and experience. Hence, our second test. About 75% of the directors in our sample are corporate executives and, therefore, it is reasonable to use the pool of corporate executives as pipelines for board directors. When merging ExecuComp and political contribution data, we find that the proportion of democratic leaning among female and minority executives range from 38.3% in 2000 to 48.6% in 2018. Controlling the supply of Democratic/Republic-leaning executives, at the state-year level, does not change the result.

The results from the two tests suggest that the documented asymmetric viewpoint inclusion, that is, Republic-leaning boards are open to include minority directors with opposite political views, but not the other way around, is more likely to be driven by

political stance of the subpopulation that serves as pipelines for board members.

ideology than by supply of talent. This mechanism implies that corporate boards will turn bluer and more/less politically diverse, each for about half of the boards, while achieving increasing demographic diversity. Our study provides one mechanism for the much-discussed issue "partisan realignment" of American business. Hersh and Shah (2023) argue that the decoupling of large businesses from the Republican coalition and toward an alignment with the Democrats, including the latter's core policy priorities, represents one of the most significant changes in American politics in decades. The realignment could be at least partly explained as a byproduct of a combination of corporations' effort to achieve more demographic diversity among its leadership and progressive boards' reluctance to admit directors with diverse viewpoints.

Finally, the Covid crisis in early 2020 serves as a laboratory for testing the significance of various aspects of board diversity in guiding firms through unforeseen challenges. It appears that experience and skill diversity emerge as the most critical and robust factors in explaining firm stock returns during the initial crisis stage of Covid.

Our paper contributes to the vast and growing literature on corporate and board diversity. As we noted earlier, our aim was to cast a wider net of diversity measures than most existing research for which the focus is usually demographic diversity, such as gender and race (e.g., Matsa and Miller, 2011; Tate and Yang, 2015; Knyazeva et al., 2021). There are a few exceptions. Adams et al. (2018) show that skill commonality (that is, lack of diversity), based on self-disclosed qualifications and skills from Regulation S-K in 2009, is associated with better firm performance. In a different setting, Lu et al. (2023) show that a broad set of diversity measures of management teams that cover academic specializations and work experiences, in addition to demographics, contribute to the performance of hedge funds. Finally, Edmans et al. (2023) develop a novel diversity, equity, and inclusion (DEI) measure using survey responses, and show that DEI as experienced by employees has little correlation with traditional diversity measures focused on gender and ethnicity, but DEI perceptions among professional workers, such as R&D employees, are significantly correlated with results, especially innovation. Our study is focused on corporate boards, adding fresh insights to DEI by integrating diversity along viewpoints, experience, skills, and institutions, and highlighting their potential impact on corporate outcomes.

2. Data and Sample Overview

2.1. Data sources

Our main databases, at the board-year level and at the director level, result from processing and merging multiple sources and covering the time period from 2000 to 2021. The first database is BoardEx, the most popular database in board governance research. During our sample period, BoardEx's coverage of U.S. public firms grows from 1,557 to 8,608 firms. BoardEx offers high-quality information at the board level (e.g, board composition and turnovers) and at the individual director level (e.g., education, achievements, and employment history).

The second database is BoardEdge, maintained by Equilar, a leading consulting firm in executive recruiting, compensation, and governance. The database covers 3,475 to 3,673 firms from 2012 to 2020 and sources its information from firms' annual shareholder reports and proxy statements. In addition to basic information, the Equilar database provides race/ethnicity information for about 16% of the directors. Importantly, the database includes the bios of individual directors (with information sourced from proxy statements and company websites). Using this textual information, we can harness richer and context-sensitive insights into the professional experience and skills of director,[3] offering a depth of

[3]The U.S. Securities and Exchange Commission (SEC) offers a regulatory framework for the disclosure of director and nominee qualifications under Item 401. This detailed textual information requires companies to delve into the individual "specific experience, qualifications, attributes, or skills" of each director and

understanding that cannot be accomplished by itemized data.

The final dataset we utilized is provided by Institutional Shareholder Services (ISS), the world's leading proxy advisory firm, which also provides data analytics related to corporate governance and investor relations. The ISS director dataset is restricted to directors of firms which were currently or recently included in the S&P 1500, and hence has a lower and less consistent coverage of firms compared to Equilar and BoardEx due to the scope and composition rebalancing of the S&P indices. ISS encompasses 12,883 to 11,938 directors from 2000 to 2021. The ISS data set provides more in-depth demographic data relative to Equilar and BoardEx, including gender, age, and tenure. Importantly for our research, the database provides information about race/ethnicity for 64% of the directors.

Our goal of composing the most comprehensive director-level data is implemented by extracting and then merging the maximum amount of information from all three databases, supplemented by additional data collection to fill in missing entries. We start with the ISS and Equilar databases, which provide us with the director-level profiles at firm-year, and then we merge them into the BoardEx database. We bridged the gaps for years where we had missing records, for example, by calculating age and time-adapting work experience. The resulting master database comprises 5,453 unique firms and 52,284 unique directors, including the 36,286 directors who entered the database during the sample period and therefore constitute the critical subsample of "new directors" for various analyzes.

In Figure 1, panels A and B show Venn diagrams for data sources for firms and directors. Panels C and D detail their time-series coverage. The number of firms/boards (with information on individual director demographic and experience) increases from 1,138 in 2000 to 3,321 in 2021. The average number of board members is 9 throughout the

nominee.

sample period, with 1.5-1.9 new board members introduced each year (and roughly the same number of departures).

[Insert Figure 1 here]

2.2. Measures for diversity

The variables that are central to our study are those that measure different dimensions of board diversity. We classify them into groups and describe them in detail. To facilitate discussion and avoid confusion, we sign and normalize all measures to be between 0 (perfectly non diverse) and 1 (perfectly diverse).

2.2.1. Demographic diversity: Gender and race/ethnicity

The first group of variables, all constructed at the firm-year level, captures board diversity based on demographics, which has also been the primary focus of the diversity literature. $\%\ Female$, i.e., the percentage of board members who are female, is the common measure for gender diversity. $\%\ Female$ grew from 9.2% to 26.2% during sample coverage.[4] For about 99% of all directors in our sample, their gender is reported in the ISS, Equilar or BoardEx databases. For observations where gender information is missing, we extract titles (e.g., Mr. or Ms.) or pronouns of directors via textual analyses or inferring from first names, resulting in a complete coding of gender.

Racial and ethnicity diversity measures, $\%\ AAPI$, $\%\ Black$, and $\%\ Hispanic$, are defined analogously. However, their classification is not trivial. The starting points of the classification are the ISS and Equilar data, which, combined, provide race/ethnicity descriptors for about 58.8% of the directors. In addition to providing direct information, this sample also serves as our training sample for classification of the remaining directors

[4] Only 0.4% of the boards are majority female. Hence $\%Female$ is monotonically and positively related to an HHI index-based diversity measure.

in the merged ISS/Equilar/BoardEx director database. After investigating the available tools, we adopt three distinct imputation methods to expand coverage and ensure accuracy in the classification of race / ethnicity.

The first tool is NamePrism, a non-commercial nationality and ethnicity classification tool developed by Ye, et al. (2017) that predicts the probability that a person is affiliated with one of the four races / ethnicities (AAPI, Black, Hispanic, and White) based on first and last names. The second tool is provided by Ethnicolor, an open-source model developed and implemented by Sood and Laohaparapanon (2018) in Python that was trained on the 2010 U.S. Census data by last name to impute ethnic probabilities into the four major racial groups, plus a combined group for two or more races. Subsequently, we re-scale (to unit) the probabilities of the four primary race/ethnicity groups. The third method supplements name-based prediction employing the facial attribute analysis tool DeepFace, proposed and publicized by Serengil and Ozpinar (2021), with director images as inputs. Portraits are not included in any of the databases; instead, we use the Google Picture API to fetch and download images based on customized queries.[5] We successfully retrieve images for 90.8% of the directors.

Using the outputs of these three methods, we develop an ensemble model that involves a supervised linear combination of the three individual estimates. In most of our analyses, we use probabilities (i.e., continuous variables) for algorithm-imputed race/ethnicity values for directors whose race/ethnicity information is not covered in the ISS data. When a single category classification (i.e., a dummy variable) is required for these observations, we use the category (AAPI, Black, Hispanic, and White) with the highest predicted probability for the classification of the dummy variable when needed. We then compare the

[5]The queries require a matching of director's name with the company's name, and the inclusion of phrases that are variants of "board director."

predicted ethnicity with the actual ethnicity dummy variables, and the resulting ensemble estimate achieves an accuracy of 93% in cross-validation-based out-of-sample tests. Internet Appendix Section IA.3 details the model optimization process. Table 1 reports the precision metrics of our ensemble out-of-sample estimates, in terms of precision (i.e., True Positives / (True Positives + False Positives)), Recall (i.e., True Positives / (True Positives + False Negatives)), and F1 score (i.e., the harmonic mean of precision and recall) which balances the trade-off between precision and recall.

[Insert Table 1 here]

A significant number of race-focused studies rely on algorithms to classify races based on names, especially with regard to the classification of Blacks. Some recent studies (e.g., Chernenko and Scharfstein, 2023) demonstrate that algorithms suffer from inaccuracy; in addition, prediction errors are at risk of being correlated with outcomes of interest. Multiple elements in our implementation mitigate the issue. First, unlike some popular methods (e.g., the Bayesian Improved First Name Surname Geocoding algorithm developed by Voicu (2018) that rely only on first names), our methods extract information from both first and last names. Second, we combine multiple algorithms, including facial recognition (leveraging the reality that photo images are usually available for highly successful people), and form an ensemble that optimizes the trade-off between precision and recall based on the training sample. As a result, the out-of-sample precision and recall rates in our training sample are both superior to those reviewed in recent studies.

The representation of the three minority groups, AAPI, Black, and Hispanic, increases from 6.6%, 1.6%, and 1.4% to 11.0%, 4.0%, and 7.2% respectively during the same period of time. Figure 2 plots the time series of demographic representation among all directors in a given year and among all new directors. Panel A plots the time series of gender representation. Panels B to D plot the representation of AAPI, Black, and Hispanic directors. Panels E and F plot the composition of all directors and all new directors in a two-way sort: White vs. non-White, and male vs. Female. Based on group classification, we are able to construct the summary variable, *Race Diversity*, to be one minus the HHI index across all four racial groups. The average value of this HHI index is 0.21.

[Insert Figure 2 here.]

2.2.2. Institutional diversity

The board literature has identified a "Rolodex" or network phenomenon (Nguyen, 2012; Cai et al., 2021) in that director appointments are often driven by "who you know," facilitated by school and professional ties to incumbent boards. Although such a pattern could be justified by coordination and search cost, it inevitably impacts diversity in more subtle ways. Social network aside, individuals who have studied in or worked for the same institution, even if not simultaneously, are often influenced by these institutions in shaping their perspectives and work approaches. Elite universities, for instance, have produced clusters of board members (Cohen et al., 2008). Prominent organizations like McKinsey, General Electric, or Goldman Sachs have so many of their former employees in leadership positions elsewhere that they are often referred to as "alumni" with distinct characteristics inherited from their professional alma mater.

To capture the effect of concentrated (or dispersed) education and employment institutions on board diversity, we construct an *InstDiversity* measure based on shared education and employment experiences. A similar method (with different grouping) is used in Lu et al. (2023). If a pair of directors on a corporate board ever attended or worked the same institution (school, employer, or service; for which concurrence is not required) outside the firm under consideration, the pair is classified to have a "connection." A normalized measure becomes the proportion of all possible pairs of directors on a board that form a connection, i.e., $InstDiversity = 1 - \sum_{i \neq j} \frac{I_{i,j}}{(n-1)n}$, where I is an indicator variable equal to one if directors i and j form a connection; and n is the total number of directors on the board. For each observation in our sample, this measure is coded using information available prior to that time point. The average value of $InstDiversity$ is 0.81. In other words, about one in five randomly selected director pairs in an average corporate board share at least one common institution in the past. Given the numerosity of universities, corporations, and organization, such a high probability signifies that corporate boards remain their own "small world."

An alternative measure, $EdDiversity$, is defined analogously, where a pair of directors form a connection if they both received their college education from similar types of institutions. Individuals who graduate from specific types of universities, such as Ivy League schools and flagship public institutions, are often influenced by distinct cultures during their formative years. These influences could potentially affect their views, styles, and resource networks later on. For education diversity, we divide all universities into ten groups: (i) "Ivy and plus,"[6] a commonly identified group of the most selective and elite higher education institutions in the U.S.; (ii) Flagship state universities; (iii) Other private comprehensive universities; (iv) Other comprehensive public universities; (v) and (vi) Specialized private and public colleagues (such as technology); (vii) Military academies; (viii) Liberal arts colleges; (ix) Two-year colleges; and (x) International universities grouped at the country level. $EdDiversity$ is then constructed analogous to $InstDiversity$. The average value is 0.53. The two measures are significantly correlated, at 0.15.

[6]This group of universities include the eight Ivy League Universities plus Stanford, MIT, Duke, and the University of Chicago.

2.2.3. Experience and skill diversity

We construct measures of experience and skill diversity from the textual biographies of directors, starting with those reported in Equilar. For directors in our sample coming from ISS and BoardEx, we script textual biographies from DEF 14A filings from SEC Edgar.[7] While firms tend to maintain a consistent style for director bios within a given year, these bios often evolve and become more detailed over time. To ensure that we extract the fullest possible information for each director, we use the latest profile for each firm-director pair (in addition to annual information) and then fill in time-adapted information for previous years.

Using textual bio information, we are able to construct *Exp Diversity*, a summary measure of experience diversity at the firm-year level. It is defined as one minus *Exp Similarity*, which is the average pairwise textual similarity between two members of the same board. If there are N directors on a board, then the average is taken over C_N^2 pairs. There have been a growing number of techniques that capture the similarity of two text bodies. We adopt two methods based on both their popularity in the literature and their current state of the art. The first and default measure is the $BERT$ (Bidirectional Encoder Representations from Transformers) similarity measure, developed by Google AI Language in 2018. Unlike traditional methods that rely on fixed word embeddings, BERT considers the entire context of words, capturing semantic nuances and producing more context-specific similarity assessments. The second and alternative measure is $TF-IDF$ (Term Frequency-Inverse Document Frequency), which assesses the importance of a word based on the idea that words that are frequent in a particular document but relatively rare in the corpus as a whole are likely to be indicative of the document's content. The $TF-IDF$ similarity measure is the cosine of the two vectors that represent each bio

[7] For details, see Internet Appendix Section IA.3.

with adjusted frequency. The averages of the two similarity measures are 0.47 and 0.12 respectively, and their correlation is 0.43.

To construct a measure of skill diversity, we first need to attribute specialized skills to individual directors. We set the universe of executive skills to include Leadership, Law, Regulation/Government, Marketing, Finance/Accounting, Operation, Technology, and Academics. For each skill, we develop a set of intuitive key keywords. Such a list is reported in the Internet Appendix Section IA.3. Because leadership quality is a prerequisite for board directorship, we narrow down the "leadership" requirement to experience as CEO or Chair of a board. Thus, each director could be represented by a vector of skills where 1 (0) indicates the presence (absence) of a particular skill. To prevent "pseudo" skill diversity created from bios that mention key words in all areas, we cap the number of skills of each director to be at most two. When a director has more than two skills mentioned in her bio, the top two are chosen based on the frequency of the keywords / phrases, as specified in Internet Appendix Section IA.3. With such a restriction, the distribution of skills among directors is as follows: 53.1% possess Finance/Accounting skill, 45.2% have expertise in leadership, 12.1% in Technology, 10.6% in Marketing, 10.1% in Law, 10.0% in Operation, 6.9% in Academics, and finally 4.3% in Regulation/Government. The cosine of two vectors measures the pairwise skill similarity, which leads to a board-level measure that is the average overall pairings. Finally, *Skill Diversity* is one minus skill similarity, with the average being 0.61.

2.2.4. Viewpoint diversity: Age and political stance

Quantifying the array of viewpoints existing within a corporate board presents a challenge given the unaccountably many aspects that shape individual values and perspectives. A practical and informative avenue to assess viewpoint diversity is through the lens of generational and political stances. Macro-level experience (such as economic depression and inflation) has been shown to shape the views and styles of corporate managers (Malmendier and Nagel, 2011, 2015), in addition to innumerable research in social and psychological research that attributes view points to specific generations. Therefore, we resort to *Age Diversity*, defined as the standard deviation of all board members normalized by the difference between the maximum and minimum age of the entire sample, as a proxy of perspectives from macro social-economic experiences. The average *Age Diversity* in our sample is 0.31.

Political stance reflects individual values that could impact reasoning and decision making. Political alignment across the group at the firm / board level also affects business operations or decisions (e.g., Duchin et al., 2019; Gormley et al., 2021; Kempf and Tsoutsoura, 2021; Dagostino et al., 2023). A common way to infer an individual's political stance is through political contributions to federally registered political committees tracked by the Federal Election Commission (FEC) (e.g., Babenko et al., 2019; Gormley et al., 2021).

In our setting, we merge the FEC individual contribution data with our director-firm-year dataset. We collected data for 384,847 director-year observations from the combined WRDS BoradEx, BoardEdge, and ISS detailed in Section 2 spanning 2000 to 2021. These data were subsequently integrated with the FEC database using director names and occupations to derive their political affiliations, Democratic, Republican, or Unaffiliated. Through this process, we successfully matched 46.97% of the director-year observations in our director database. Our matching criteria require a full name match for directors. When there is ambiguity, we further require at least one positive match from either their employer or location. Because directors often have multiple affiliations over time, possibly spanning multiple locations, we take into account the employment history for each director when matching to the FEC data at the director-contributor(FEC)-location-year level.

Let $D_{i,t}$ and $R_{i,t}$ be the number of Democratic and Republican leading directors for the observation of the year of the firm $i.t$, and let $N_{i,t}$ be the sum of the two. Then the standard HHI index is $(D_{i,t}/N_{i,t})^2 + (R_{i,t}/N_{i,t})^2$. Due to the small number of categories, the best practice is to adjust the index to be: $(N_{i,t} \times \text{HHI}_{i,t} - 1)/(N_{i,t} - 1)$.[8] The adjusted HHI of affiliations to the two main parties becomes our measure of political diversity, $Pol\ Diversity$. The average $Pol\ Diversity$ in our sample is 0.46.

Figure 3 plots the time series of all diversity measures discussed in this section. The growth of racial diversity is highly visible, with a particularly notable acceleration during the last few years of the sample period. Both experience and skill diversity slightly trended down. That is, boards are recruiting directors with increasingly similar resumes and human capital. Political diversity has remained more or less constant. Finally, age diversity decreases up to the mid-2000s and then increases significantly since 2006. The first phase was driven by the aging of directors during a relatively low turnover period, and the second phase has been driven by the increasing presence of relatively young board directors.

[Insert Figure 3 here.]

2.3. Other board/firm characteristics and summary statistics

Our sample consists of 5,453 unique firms during 2000-2021. Firm-year level characteristics are retrieved from WRDS. Next, we describe the most common variables that are included in the analyses in the board literature. The first variable is firm market capitalization, $Market\ cap$, the average (median) value is \$14.7 billion (\$1.9 billion) in 2021. We use the logarithmic value in regressions to mitigate skewness. The second variable is the number of years since the firm IPO, $Firm\ age$, where the average (median) value is 22.6

[8] See Hall, Jaffe and Trajtenberg (2001).

(18.0) years. The third variable is the number of directors on a board, *Board size*, where the average and median values are nine. Finally, we classify a firm's industry affiliation at the three-digit SIC level, $SIC3$, unless otherwise specified, there were 237 unique $SIC3$ classifications covering our sample firms in 2021.

3. Overview of Board Diversity

We begin a correlational analysis of board diversity by studying the relationships between measures of diversity introduced in the previous section. Panel A of Table 2 presents Pearson correlations across diversity measures. In panel B, we regress each measure on board and firm characteristics, as well as year and industry fixed effects. We find that some characteristics of the board and the firm have a monotonic relationship with diversity measures. For example, firm market cap is negatively correlated with almost all measures. However, other characteristics drive measures of board diversity in opposite directors. For example, board characteristics such as $\%Female$ and $\%Black$ have a positive association with political stance Diversity and negative association age diversity. Thus, Table 2 reveals that board diversity is a multidimensional object with trade-offs among various aspects of diversity.

[Insert Table 2 here.]

Next, we focus on the contribution of new directors' characteristics to board diversity. Studying this source of variation in board diversity is useful because changes in board diversity induced by new director appointments are more precise measurements of actions taken by firms. In Table 3, where observations are at the new director level at the year of their addition to the boards, the dependent variable is the change in a diversity measure (that is not based on gender and race) of a corporate board with the addition of the new director. The independent variables are individual characteristics pertaining to gender and race, where White male directors as a group serve as the omitted category in the regression with industry fixed effects.[9] A positive coefficient is indicative of enhanced board diversity along specific dimensions when a new director joins the board.

[Insert Table 3 here.]

Table 3 shows that the addition of gender- and race-minority directors of all groups is associated with significantly enhanced board diversity in experience, skill, age, and institutions (with the exception of insignificance of AAPI directors toward institutional diversity). For instance, adding a female director leads to an average of 0.269 increase in *Skill Diversity*, or a 0.137 increase in *Institution Diversity*. Relative to the cross-sectional standard deviation of 0.0484 and 0.0480, these are material impacts. The age diversity effect is likely driven by the fact that minority directors tend to be younger. For example, female new directors average 55.4 years old, while the incumbent average age is 62.

The relation between demographics and other measures of diversity is less clear. Only the addition of new Black directors is associated with expanding political stances of board members, while other groups bring insignificant changes. It also seems that new female and Black directors are more likely to share the same education background as incumbents (driven by common elite education backgrounds), while Hispanic new directors are most likely to have received education from different types of universities. Overall, with the exception of education background, we find a positive relationship between new directors' characteristics that capture demographic diversity and changes in board diversity measures along non-demographic dimensions. This is consistent with Erel et al. (2021) that shows

[9]Because the dependent variables are first differences (changes in diversity), fixed effects along the time dimension, such as a yearly fixed effect, are subsumed.

a positive relation between demographic diversity and machine-learning predicted director performance.

In our sample, about 40% of the new directors replace a departing board member, and the rest of the newly added directors effectively expand the board size. Table IB.1 in the Online Appendix describes the contribution of the new director to the diversity of the board, conditional on expansions and replacements. We find that the relationship between changes in diversity measures and new directors' characteristics that capture ethnic diversity does not differ based on whether a new director is added to replace a departing director or to expand board size.

4. Political Stance Diversity for Democratic- and Republic- Leaning Boards

Given the increasing political polarization of corporate America, we further divide the sample into boards (at the firm-year level) dominated by Republican or Democratic leaning directors. We call a board to be democratic or progressive-leaning if there are more directors who contribute to Democratic candidates and Democratic-leaning committees than those who contribute to Republican ones. Vice versa for Republican- or conservative-leaning boards. In other words, the political stances of boards are classified based on partisan affiliations. This practice is common in the literature on political stances and political polarization between U.S. corporations (e.g., Duchin et al., 2019; Fos et al., 2023).

Table 4 reports the results and points to a curious contrast. In both types of boards, gender/racial minority directors contribute positively to experience and skill diversity, but their impacts on a board's political stance diversity are opposite from each other. Specifically, Republican-leaning boards appoint new gender and racial minority directors who are more likely to be from the opposite political spectrum, while Democratic-leaning boards appoint new minority directors who are more likely to hold similar political views as the incumbents. The contrast effect is the most prominent among new female directors: the coefficient of $Female$ is 0.188 for a Republican leaning board and -0.151 for a Democratic leaning board, both of which are significant at the 1% level. A similarly significant set of opposite effects is present for Black and AAPI directors. In other words, when a female, or Black, or Asian is recruited to a board, the new director is significantly more likely than a new White director to be a political minority to the board if the current board is Republic leaning. The same type of gender and racially diverse directors are more likely to be politically conforming to the incumbents if the board is Democratic leaning. Hispanic new directors, on the other hand, contribute to political diversity in ways similar to White colleagues for Democratic leaning boards. Their contribution to the political diversity of Republican leaning boards is positive.

[Insert Table 4 here.]

We next compare the relationship between new director characteristics and the likelihood that the director is a political minority for boards dominated by Republican or Democratic leaning directors. Specifically, we run a regression at the new director level and interact with the characteristics of the new director with $DemMaj$, which takes a value of one if the board has more Democratic-leaning directors than Republican ones. Table 5 reports the results and confirms that Democratic-leaning boards appoint new minority directors who are more likely to have similar political views. Taking column (2) as an example, the coefficient of $Black$ is 0.0728, indicating that when a Black director is newly recruiting by a Republican leaning boards (for which the $DemMaj$ dummy variable is zero), the director is 7.28% more likely to be a political minority (i.e., being Democratic leaning). The interaction of $Black \times DemMaj$, however, is -0.152, indicating that Democratic-leaning boards offset the effect by 15.2%, resulting in a lower (than par) likelihood of a new Black directors being a political minority (i.e., holding Republican political views).

Such offsetting effects are significant among Democratic-leaning boards for all groups of demographically diverse directors (women and all racial minorities).

[Insert Table 5 here.]

This finding indicates that there is a tension between demographic and political diversity, but only in an asymmetric way. For Republican-leaning boards, demographic and political stance diversity go hand in hand: adding a new director who is a demographic minority also contributes to board's Political Stance Diversity. On the contrary, adding a new director who is a demographic minority makes Democratic-leaning boards less politically diverse. That is, Democratic-leaning boards are more inclusive of demographically diverse new directors if the latter are aligned with the political views of the incumbents.

Our findings imply that as corporate boards become more gender and racially diverse, we expect conservative leaning boards to become more balanced and progressive leaning boards to become more homogeneous over time. Moreover, all corporate boards are evolving in a progressive direction while becoming more diverse demographically. Such a contrast and trend could not have been inferred from the aggregate sample that pools the two types of boards and has not been noted in either research or commentaries.

The opposite evolution of political diversity between the two groups of boards involves appointing progressive-leaning minority directors. Thus, it could be argued that corporate boards merely accommodate the supply of female and minority candidates who are perceived to be progressive-leaning candidates. To evaluate to what extent this hypothesis drives out result, we perform two tests based on the idea that to the extent that the supply of directors is affected by the local labor market, we can control for the composition of political views of potential board members.

In the first test, we check whether Democratic-leaning firms in "red" states recruit more minority directors who are on the other side of political stances than those residing in "blue" states, where we use the most recent Presidential election to classify "red" and "blue" states. Table 6 reports the results. Two key findings emerge. First, we find that whether the state is a Democratic or a Republican majority state is irrelevant. Specifically, columns (1) and (3) show that when we condition the analysis on Republican-leaning boards, the results are very similar for both types of states. Similarly, columns (2) and (4) indicate that the political stance of the state does not have a profound effect on the results when we condition the analysis on Democratic-leaning boards. Thus, the more likely explanation for our findings is that the results are driven by board's political views, rather by supply of directors.

[Insert Table 6 here.]

Next, we introduce the second test to address any limitation to political inclusion due to the supply of diverse director candidates. About 75% of the directors in our sample are corporate executives and, therefore, it is reasonable to use the pool of corporate executives as pipelines for board directors. By merging the executive data from ExecuComp with political contributions, we find that, among female and racial minority executives, the proportion of democratic-leaning ranges from 38.3% in 2000 to 48.6% in 2018. Figure 4 presents these results. Nationally, a substantial proportion of minority senior executives are conservative leaning. Internet Appendix Figure IB.1 shows that the fraction of Democratic directors ranged from 30% to 40% during the sample period. For non-white male directors, the fraction of Democratic directors ranged from 40% to 50%.

[Insert Figure 4 here.]

It turns out that controlling for the percentage of such directors at the state-year level does not change the result. The results in columns (5) through (8) of Table 6 show that the results remain when we control for the share of Democratic executives and non-white male Democratic executives in the state. That is, controlling for the percentage of such directors at the state-year level does not change the result. Moreover, there is a slight difference in the "pipeline effect" as shown in the last two columns of the table: Republic-leaning boards' recruitment of politically diverse directors is not at all affected by the local supply of progressive-leaning candidates; but Democratic boards are slightly so (at the 10% significance level).

In Table 7 we pool Democratic and Republican-leaning firms and show that demographic characteristics continue to play a significantly different role in the diversity of board political positions for two types of firms. The interaction terms between demographic characteristics and $DemMaj$ demonstrate that the differences between the two types of boards sorted by political stances are statistically significant.

[Insert Table 7 here.]

5. Do diverse directors fit in?: Evidence from departures

When a new director brings diversity to a board, they often find themselves in the minority along the same dimension that defines their diversity. Within an established culture shaped by incumbents, the question arises: Do diverse directors fit in? This query can be explored through the lens of the probability of attrition. Not all departures signify negative outcomes. Successful directors who possess unique resources and skills may find themselves in high demand elsewhere and are poached for higher positions. For this reason, we consider three potential outcomes contingent on attrition: departures to better positions, departures to lesser positions, and other departures. Specifically, a "better (lesser) position" is characterized by a new affiliation (a board member or senior executive) with a firm that is at least 25% larger (smaller) in market capitalization compared to the current firm, or a new position that is a clear promotion (demotion) in terms of seniority, all within a two-year time frame. "Other departures" encompass moves to comparable firms or those without definitive information. Such a setting of attrition involving multiple potential outcomes could be analyzed using a multinomial logit model.

Table 8 reports the results. The unit of observation is at the director-year level and the base outcome category is defined as a director maintaining their position on the board. There are two regressions reported in the table, each taking up three columns indicating the sensitivity of a particular outcome conditional on departure with respect to the same set of independent variables. For example, the first column of each regression indicates how each covariate is associated with the odds of departing to a better position, relative to staying put. All coefficients are odds ratios with a null value of one, and significance levels are marked based on the difference between the coefficient and the null.

[Insert Table 8 here.]

Regression (1) shows Female directors are 8.6% more likely to depart to a better position, but 85% less likely to depart to a lesser position, and 26% less likely to make a lateral move. All coefficients are statistically significant. A similar pattern is observed among Black directors. Hispanic directors are much less likely to leave for lesser positions, and AAPI directors are more likely to make lateral moves. Given that all demographic minority groups are less likely than white males to be in attrition for unfavorable causes, it shows that these directors are well retained by their current boards. Moreover, the results also suggest that minority directors, especially famale and Black directors, are highly valued by the labor market.

In the second regression, we add variables that capture the contribution of a director to the current firm along other diversity measures associated with experience, political stance, skill, institution, and education. Note that a director that is skill-diverse to the current board may or may not be so in the destination board to which they depart, hence the column that we are most interested in is the one associated with "Lesser Positions." A significantly higher odds of a "lesser" departure would signal that the director did not succeed in the current board. Encouragingly, none of the coefficients associated with these additional diversity measures is significantly greater than one.

6. Board diversity and crisis management

In the dynamic landscape of modern business, crises present unique challenges that demand astute leadership and decision-making. Thus, firms' performance during the unforeseen Covid crisis serves as a setting to test whether board diversity matters in such an unusual time. We pin down the "crisis time" to be February to March 2020 because the U.S. market (e.g., S&P 500 Index started a series of large daily declines from February 24, until March 20, the day before the $2.2 trillion fiscal stimulus gained traction.

In particular, we construct two performance measures for the "crisit test." The first is an industry (at the SIC three-digit level) adjusted stock return. The second is risk-factor adjusted stock return using the method developed in Daniel, Grinblatt, Titman and Wermers (1997) ("DGTW"). The original DGTW measure benchmark against $5 \times 5 \times 5$ portfolios sorted by size, book-to-market, and momentum. Because the Covid stock market crash was also a liquidity event, we adopt a $3 \times 3 \times 3 \times 3$ sorting with liquidity added using the Amihud (2002) illiquidity measure, following Da, Gao and Jagannathan (2011a). Independent variables include all diversity measures developed in this study.

Table 9 reports estimates of a cross-sectional regression of firm abnormal stock returns on board diversity characteristics. In Panel A, we use Fama-French 48 industry-adjusted returns as the firm performance measure. Because the returns are already de-meaned at the industry level, the regression does not contain industry fixed effects. Several significant results emerge. First, both gender and racial diversity measures are statistically significant. we find that Gender Diversity is associated with worse stock performance. This association could be explained by the negative impact of Covid on professional women documented in other studies (e.g., Da et al. (2011b), Barber et al. (2021)). Because most of the studies on the gender effect of Covid attribute the main effect to heightened family care especially child care burden (usually proxied by age between 30 and 50), in column (6) we control for percent of female director under the age of 50 (almost none of the female directors are under 30) but found that the gender effect could not be explained by child care burden brought by Covid for the population of directors. In contrast, we find that Racial Diversity is associated with better stock performance in all regressions.

[Insert Table 9 here.]

Next, both experience and skill diversities are correlated with significantly improved stock returns during times of crisis. With firms compelled to swiftly adjust to remote work, there was a peak demand for technology skills, as confirmed in column (6), which indicates that a greater proportion of directors with technology skills was linked with elevated stock returns. Importantly, however, the presence of technology skills does not replace or diminish the impact of skill diversity. Lastly, diversity in educational backgrounds emerges as a negative factor, for which we do not have a clear explanation.

In Panel B, the dependent variables comprise stock returns benchmarked against portfolio returns sorted by size, book-to-market, momentum, and liquidity. All regressions incorporate industry fixed effects. In comparison to the findings in Panel A, measures of gender, racial, and education diversity have all lost significance. This suggests that firms with boards exhibiting diverse demographic characteristics may have distinct loadings on common risk factors in systematic manners. Such disparity between the two panels underscores the caution required when inferring significant correlations between firm performance and demographic diversity among leadership, a topic that has garnered significant attention in research.

With the risk factor adjustment, experience and skill diversity retain their positive significance in explaining firm stock returns during the initial crisis stage of Covid. The robustness of these two measures underscores that boards matter and that firms guided by boards possessing all-round and complementary experiences and skills are better equipped to navigate an unexpected shock of unforeseen nature.

7. Conclusion

Based on a newly constructed and comprehensive database of board directors, this study provides a multidimensional perspective on the state of diversity within U.S. public firm boards. We would like to provide three concluding remarkes. First, while we observe significant progress in demographic diversity, particularly in terms of gender and race/ethnicity, the same cannot be said for diversity in experience, skill, and viewpoints as measured political stance.

Second, whereas the growing presence of gender and racial minority directors enhances experience and skill diversity within boards, it has an uneven impact on viewpoint diversity. The addition of demographically diverse directors is associated with an increase (decrease) in the diversity of political stance among the "red" ("blue") boards, resulting in "bluer" boards for both groups. This novel outcome suggests a potential mechanism contributing to the noted "partisan realignmen" of Corporate America over the past two decades.

Thirdly, the Covid crisis serves as a laboratory for testing the significance of various aspects of board diversity in guiding firms through unforeseen challenges. It appears that experience and skill diversity emerge as the most critical factors in this regard.

References

Adams, R.B., Akyol, A.C., Verwijmeren, P., 2018. Director skill sets. Journal of Financial Economics 130, 641–662.

Adams, R.B., Ferreira, D., 2009. Women in the boardroom and their impact on governance and performance. Journal of Financial Economics 94, 291–309.

Ahern, K.R., Dittmar, A.K., 2012. The Changing of the Boards: The Impact on Firm Valuation of Mandated Female Board Representation. The Quarterly Journal of Economics 127, 137–197.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Autor, D., Dorn, D., Hanson, G., Majlesi, K., 2020. Importing political polarization? the electoral consequences of rising trade exposure. American Economic Review 110, 3139–83.

Babenko, I., Fedaseyeu, V., Zhang, S., 2019. Do CEOs affect employees' political choices? Review of Financial Studies 33, 1781–1817.

Barber, B., Jiang, W., Morse, A., Manju, P., Tookes, H., Werner, I.M., 2021. What explains differences in finance research productivity during the pandemic? Journal of Finance 76, 1655–1697.

Bernile, G., Bhagwat, V., Yonker, S., 2018. Board diversity, firm risk, and corporate policies. Journal of Financial Economics 127, 588–612.

Bertrand, M., Kramarz, F., Schoar, A., Thesmar, D., 2018. The Cost of Political Connections. Review of Finance 22, 849–876.

Bian, B., Li, J., Li, K., 2023. Does mandating women on corporate boards backfire? Working paper.

Boxell, L., Gentzkow, M., Shapiro, J.M., 2023. Cross-country trends in affective polarization. Review of Economics and Statistics forthcoming.

Cai, J., Nguyen, T., Walkling, R., 2021. Director Appointments: It Is Who You Know. The Review of Financial Studies 35, 1933–1982.

Cai, W., Dey, A., Grennan, J., Pacelli, J., Qiu, L., 2022. Do diverse directors influence dei outcomes? Working paper.

Chernenko, S., Scharfstein, D., 2023. The limits of algorithmic measures of race in studies of outcome disparities. Working paper.

Cohen, L., Frazzini, A., Malloy, C., 2008. The small world of investing: Board connections and mutual fund returns. Journal of Political Economy 116, 951–979.

Cziraki, P., Robertson, A., 2023. When bill rolls off: Continuity and change on corporate boards. Working Paper.

Da, Z., Gao, P., Jagannathan, R., 2011a. Impatient trading, liquidity provision, and stock selection by mutual funds. Review of Financial Studies 24, 675–720.

Da, Z., Gao, P., Jagannathan, R., 2011b. Locked-in at home: The gender difference in analyst forecasts after the covid-19 school closures. Journal of Accounting and Economics 76, Open access.

Dagostino, R., Gao, J., Ma, P., 2023. Partisanship in loan pricing. Journal of Financial Economics forthcoming.

Daniel, K., Grinblatt, M., Titman, S., Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. The Journal of Finance 52, 1035–1058.

Duchin, R., Farroukh, A.E.K., Harford, J., Patel, T., 2019. Political attitudes, partisanship, and merger activity. Working Paper.

Eckbo, B.E., Nygaard, K., Thorburn, K.S., 2022. Valuation effects of norway's board gender-quota law revisited. Management Science 68, 4112–4134.

Edmans, A., Flammer, C., Glossner, S., 2023. Diversity, equity, and inclusion. ECGI Finance Working Paper 913/2023.

Erel, I., Stern, L.H., Tan, C., Weisbach, M.S., 2021. Selecting Directors Using Machine Learning. The Review of Financial Studies 34, 3226–3264.

Field, L.C., Souther, M.E., Yore, A.S., 2020. At the table but can not break through the glass ceiling:board leadership positions elude diverse directors. Journal of Financial Economics 137, 787–814.

Fos, V., Kempf, E., Tsoutsoura, M., 2023. The Political Polarization of Corporate America. Working paper.

Giannetti, M., Wang, T.Y., 2023. Public attention to gender equality and board gender diversity. Journal of Financial and Quantitative Analysis 58, 485–511.

Gormley, T., Jha, M., Wang, M., 2023a. The politicization of social responsibility. Working Paper.

Gormley, T.A., Gupta, V.K., Matsa, D.A., Mortal, S.C., Yang, L., 2023b. The big three and board gender diversity: The effectiveness of shareholder voice. Journal of Financial Economics 149, 323–348.

Gormley, T.A., Kaviani, M., Maleki, H., 2021. When do judges throw the book at companies? The influence of partisanship in corporate prosecutions. Working Paper.

Griffin, D., Li, K., Xu, T., 2021. Board gender diversity and corporate innovation: International evidence. Journal of Financial and Quantitative Analysis 56, 123–154. doi:10.1017/S002210901900098X.

Hall, B.H., Jaffe, A.B., Trajtenberg, M., 2001. The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools. Working Paper 8498. National Bureau of Economic Research.

Hersh, E., Shah, S., 2023. Who wants stakeholder capitalism? Public and elite perceptions of the role of business in politics. Working Paper.

Howard, K.A., Cervone, D., Motyl, M., 2022. On the varieties of diversity: Ideological variations in attitudes toward, and understandings of diversity. Personality and Social Psychology Bulletin 48, 1039–1053.

Iyengar, S., Sood, G., Lelkes, Y., 2012. Affect, not ideology. Public Opinion Quarterly 76, 405–431. URL: https://ezproxy.cul.columbia.edu/login?qurl=https%3a%2f%2fsearch.ebscohost.com%2flogin.aspx%3fdirect%3dtrue%26db%3dsih%26AN%3d82329251%26site%3dehost-live%26scope%3dsite.

Jiang, W., 2023. Diversity through turnover: How to overcome the glacial pace toward board diversity? Journal of Law, Finance, and Accounting 7, 1–26.

Kempf, E., Tsoutsoura, M., 2021. Partisan professionals: Evidence from credit rating analysts. Journal of Finance 76, 2805–2856.

Kim, D., Starks, L.T., 2016. Gender diversity on corporate boards: Do women contribute unique skills? American Economic Review 106, 267–71.

Knyazeva, A., Knyazeva, D., Naveen, L., 2021. Diversity on corporate boards. Annual Review of Financial Economics 13, 301–320.

Lu, Y., Naik, N.Y., Teo, M., 2023. Diverse hedge funds. The Review of Financial Studies 37, 639–683.

Malmendier, U., Nagel, S., 2011. Depression Babies: Do Macroeconomic Experiences Affect Risk Taking? The Quarterly Journal of Economics 126, 373–416.

Malmendier, U., Nagel, S., 2015. Learning from Inflation Experiences. The Quarterly Journal of Economics 131, 53–87.

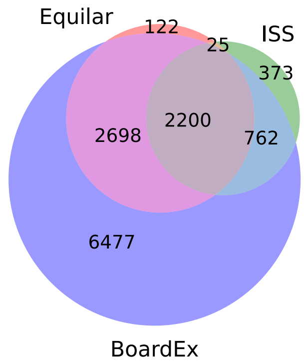
Mason, L., 2015. I disrespectfully agree: The differential effects of partisan sorting on social and issue polarization. American Journal of Political Science 59, 128–145.

Matsa, D.A., Miller, A.R., 2011. Chipping away at the glass ceiling: Gender spillovers in corporate leadership. American Economic Review 101, 635–39.

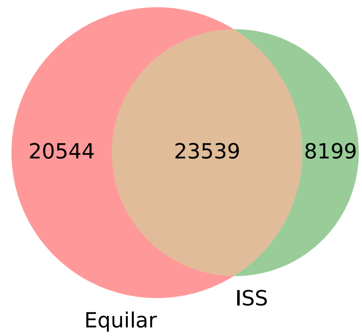
Nguyen, B.D., 2012. Does the rolodex matter? corporate elite's small world and the effectiveness of boards of directors. Management Science 58, 236–252.

Tate, G., Yang, L., 2015. Female leadership and gender equity: Evidence from plant closure. Journal of Financial Economics 117, 77–97.

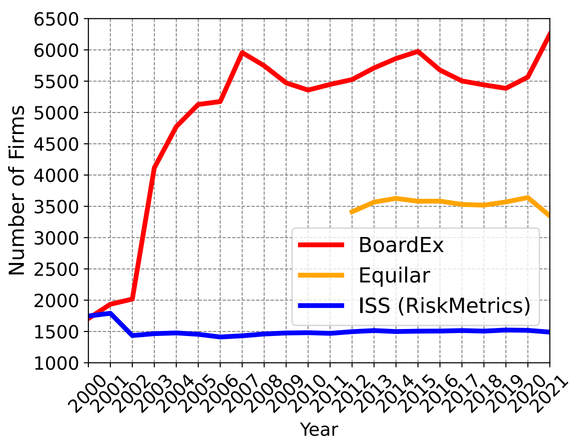
Voicu, I., 2018. Using first name information to improve race and ethnicity classification. Statistics and Public Policy 5, 1–13.



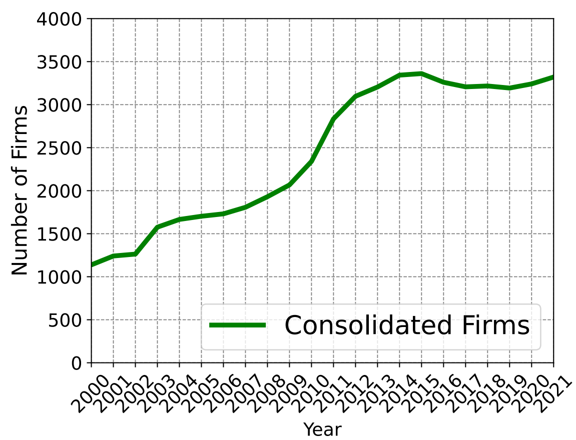
Panel A: Firms



Panel B: Directors



Panel C: Firms



Panel D: Consolidated Firms

Figure 1: **Venn diagrams and time series of number of firms and directors in BoardEx, ISS, and Equilar.** In Panel A on the upper left, the intersection of firms is displayed. Our focus is on the overlap between BoardEx and the union of Equilar and ISS since the latter two provide profiles for experience diversity. Panel B on the upper right depicts the directors from our consolidated dataset. Panel C shows the evolution of firm coverage within the BoardEx, Equilar, and ISS. Panel D illustrates the consolidated number of firms for which demographic information and textual bios of directors are assembled.

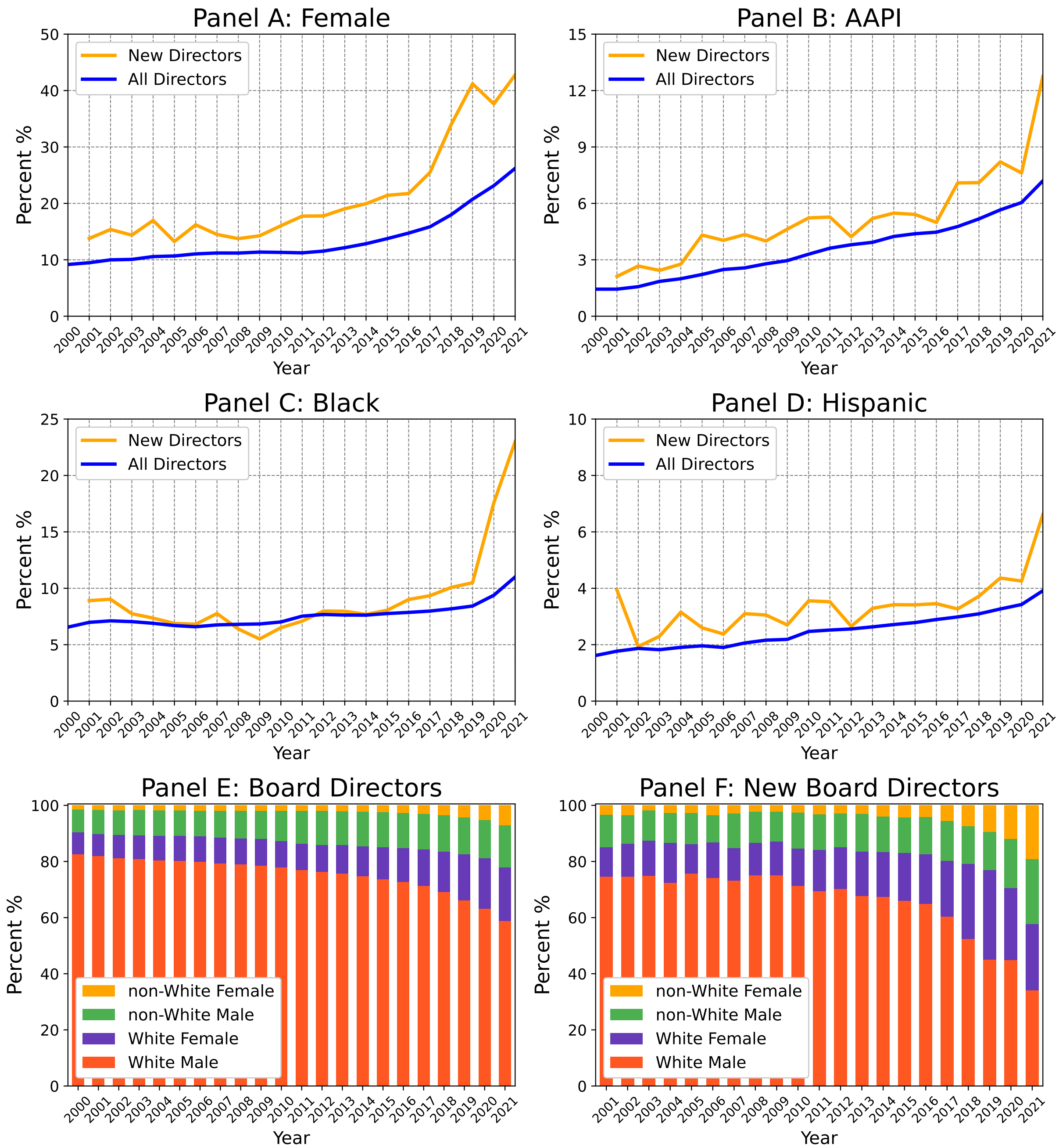


Figure 2: **Time Series of Gender and Race Representation on Boards.** Panel A plots the time series of gender representation. Panels B to D plot the representation of APPI, Black, and Hispanic directors. Panels E and F plot the composition of all directors and all new directors in a two way sorts: White vs. non-White, and male vs. female.

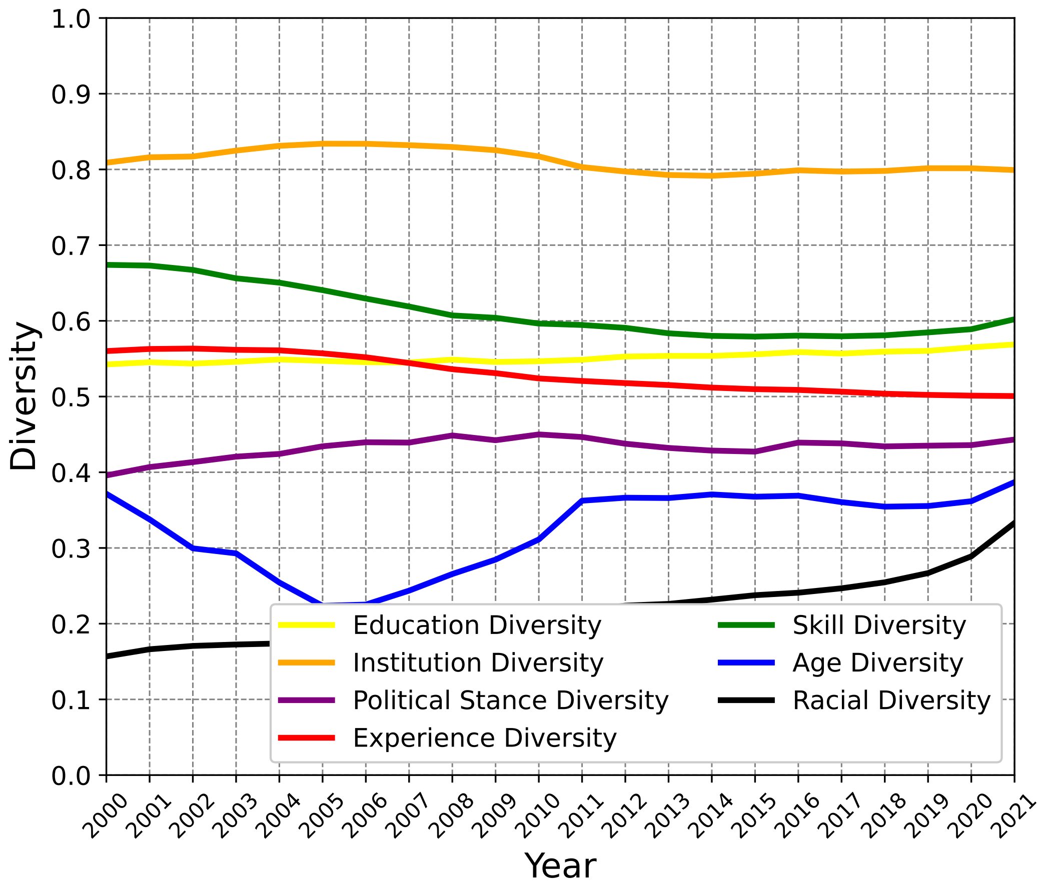
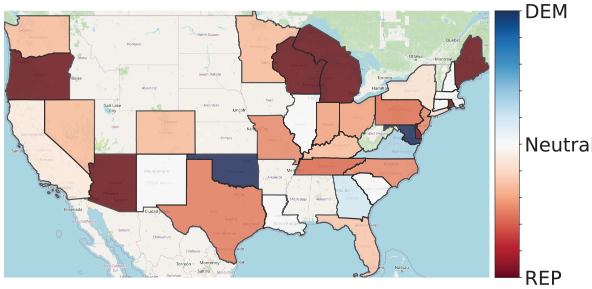
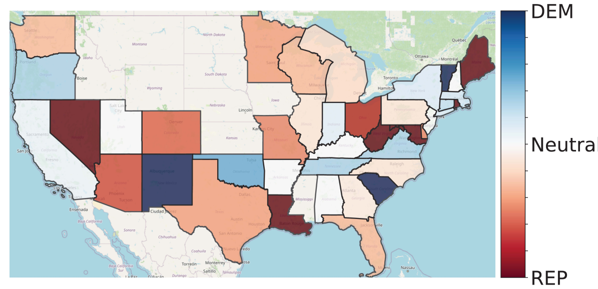


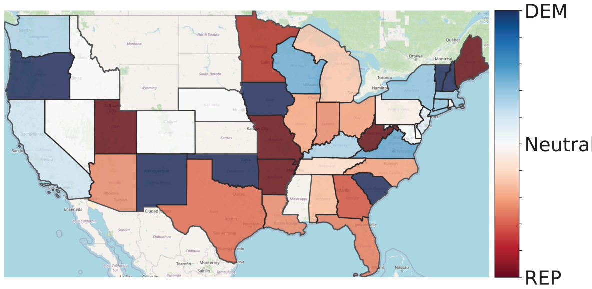
Figure 3: **Time Series of Board Diversity Measures.**



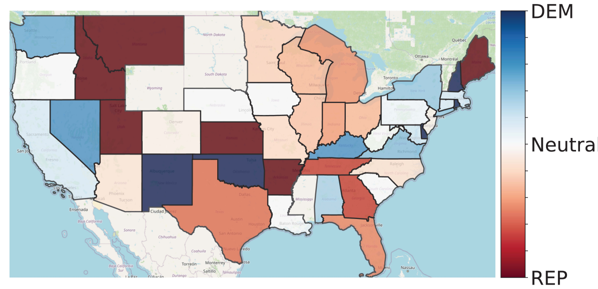
(a) Year 2000



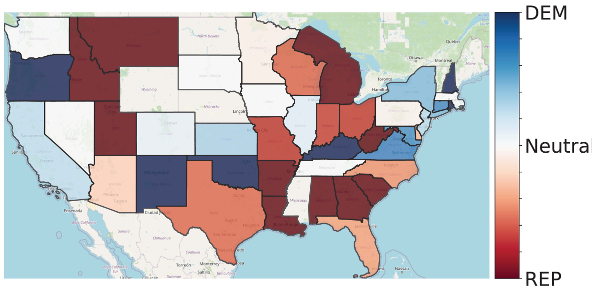
(b) Year 2004



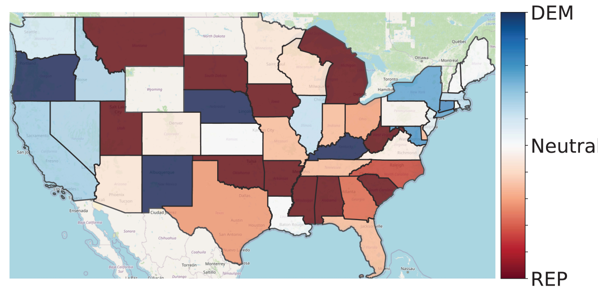
(c) Year 2008



(d) Year 2012



(e) Year 2016



(f) Year 2018

Figure 4: **Minority or Female Political Stance across years.** The political stance for each state-year was determined by the proportion of executives affiliating with the Democratic party. A value of 0% (represented by the color red) represents complete Republican-leaning executives, while 100% (in blue) indicates a total Democratic bias. A neutral stance, where affiliations are evenly split, is depicted in white.

	AAPI	Black	Hispanic	White
Precision	0.86	0.75	0.83	0.95
Recall	0.82	0.57	0.65	0.98
F1 score	0.84	0.65	0.73	0.96
Support	570	738	286	8406

Table 1: **Ensemble prediction of out-of-sample ethnicity measures.**

Table 2: **Measures of diversity.** The unit of observations is at the firm-year level. Panel A documents Pearson correlations across seven diversity measures. In columns (1), the dependent measure *Experience Diversity* is defined as one minus the average cosine similarity of Sentence-BERT model embeddings, and for column (2) it is based on one minus the average cosine similarity of the Skill representations. In column (3), the dependent variable is *Political Stance Diversity*, defined as one minus the adjusted HHI(Herfindahl–Hirschman Index) of political stances among directors at the firm-year level. In column (4), the dependent variable is *Racial Diversity*, defined as one minus HHI of four ethnicities: AAPI, Black, Hispanic and White. In column (5), *Education Diversity* is measured by dividing universities into 10 groups and calculating the proportion of board directors sharing the same educational background, e.g., $EduDiversity = 1 - \sum_{i \neq j} \frac{I_{i,j}}{(n-1)n}$, where I is an indicator variable equal to one if directors i and j form a same education group; and n is the total number of directors on the board. In column (6), *Institution Diversity* reflects shared educational and employment experiences, evaluating if directors have common histories with any institutions, regardless of concurrent attendance or employment. In column (7), *Age Diversity* is defined as a linear transformation of the standard deviation of the board member ages, more specifically, $\text{age diversity}_{i,t} = \frac{1}{3} \cdot \sqrt{\frac{\sum_{j=1}^{k_i} \left(\text{age}_{i,j,t} - \overline{\text{age}}_{i,t}\right)^2}{k_i - 1}} - 2.4$ for firm i at time t consisting of k_i directors from $j = 1, \ldots, k_i$. Lastly, in column (8), *Gender Diversity* is represented by the HHI index of the percentages of male and female directors at the firm-year level. Panel B provides a summary of the regression analyses where Experience diversities, Skill diversity, and Political stance diversity serve as dependent variables, regressed on demographic average director age (*Avg Director Age*), female percentage (*%Female*), four ethnicities, and firm-specific characteristics (board size, market capitalization, firm age). The sample covers 52,980 firm-year observations. Standard errors are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Pearson Correlations of Diversity Measures

	Experience Diversity (1)	Skill Diversity (2)	Political Stance Diversity (3)	Racial Diversity (4)	Education Diversity (5)	Institution Diversity (6)	Age Diversity (7)	Gender Diversity (8)
(1) Experience Diversity	1.000							
(2) Skill Diversity	0.224	1.000						
(3) Political Stance Diversity	0.009	-0.017	1.000					
(4) Racial Diversity	-0.088	0.013	0.028	1.000				
(5) Education Diversity	-0.033	-0.022	-0.001	0.022	1.000			
(6) Institution Diversity	0.168	0.060	0.028	-0.084	0.121	1.000		
(7) Age Diversity	0.008	0.030	-0.013	0.022	0.005	-0.055	1.000	
(8) Gender Diversity	-0.034	0.024	0.042	0.131	-0.018	0.058	-0.143	1.000

Panel B: Regression of Diversity on Demographic and Firm Characteristics

	Experience Diversity (1)	Skill Diversity (2)	Political Stance Diversity (3)	Education Diversity (4)	Institution Diversity (5)	Age Diversity (6)
%Female	0.00522	0.0827***	0.0364***	-0.0263**	0.0555***	-0.125***
	(0.0122)	(0.0116)	(0.0109)	(0.0131)	(0.0117)	(0.00991)
%Black	0.0161	0.0254**	-0.000662	-0.00849	-0.0134	-0.0261***
	(0.0106)	(0.0114)	(0.0102)	(0.0121)	(0.00999)	(0.00877)
%AAPI	-0.0298**	0.0138	-0.00646	-0.00615	-0.0186	0.0300***
	(0.0127)	(0.0108)	(0.0118)	(0.0139)	(0.0119)	(0.0105)
%Hispanic	0.0262**	0.0157	0.0109	0.0359**	0.0193*	0.0128*
	(0.0113)	(0.0122)	(0.0103)	(0.0142)	(0.0109)	(0.00768)
Avg Director Age	0.0517***	0.128***	0.00662	-0.0456***	0.0161	
	(0.0127)	(0.0124)	(0.0116)	(0.0143)	(0.0123)	
Board Size	0.0221*	0.0654***	0.0115	0.0122	-0.0632***	0.0475***
	(0.0132)	(0.0142)	(0.0110)	(0.0146)	(0.0134)	(0.0116)
Market Cap	-0.0817***	-0.126***	0.0241**	-0.00145	-0.0364***	-0.151***
	(0.0148)	(0.0134)	(0.0121)	(0.0140)	(0.0127)	(0.0111)
Firm Age	0.148***	-0.0347***	-0.0146	-0.0290**	0.318***	-0.0599***
	(0.0132)	(0.0131)	(0.0113)	(0.0134)	(0.0124)	(0.0104)
Observations	53,096	53,096	45,325	52,922	53,094	53,096
Adjusted R^2	0.231	0.223	0.0385	0.0833	0.207	0.137
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 3: **The contribution of new director to board diversity.** The unit of observations is at the new director level containing 36,286 new directors between 2001 and 2021. The dependent variables reflect changes in five diversity dimensions resulting from the addition of these new directors. *Female* is the dummy variable of gender, where a value of one indicates female; *Black*, *AAPI*, and *Hispanic* are predicted ethnicity probability from ensemble method defined in 2.2.1. Firm control variables include firm age, board size, and market capitalization. The age of the new director is accounted for in the measures of Political Stance, Experience, and Skill. However, age control is excluded for ΔAge Diversity, as age itself is the variable of response in this measure. Standard errors, presented in parentheses, are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are standardized by subtracting the mean and dividing by the standard deviation and each coefficient represents the sensitivity to a one standard deviation increase in the corresponding independent variable.

	ΔPolitical Stance Diversity (1)	ΔExperience Diversity (2)	ΔSkill Diversity (3)	ΔEducation Diversity (4)	ΔInstitution Diversity (5)	ΔAge Diversity (6)
Female	0.0188	0.196***	0.269***	-0.0673***	0.137***	0.0125***
	(0.0138)	(0.0123)	(0.0123)	(0.0118)	(0.0119)	(0.00418)
Black	0.0145**	0.0423***	0.0508***	-0.0248***	0.0150***	0.00508***
	(0.00596)	(0.00487)	(0.00507)	(0.00470)	(0.00452)	(0.00165)
AAPI	-0.00260	0.0356***	0.0254***	0.00741	0.00152	0.0237***
	(0.00561)	(0.00613)	(0.00548)	(0.00541)	(0.00574)	(0.00214)
Hispanic	0.00443	0.0475***	0.0173***	0.00956**	0.00846*	0.00424***
	(0.00539)	(0.00535)	(0.00545)	(0.00487)	(0.00453)	(0.00155)
Observations	30,882	36,000	36,000	35,928	35,998	36,000
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Control	Yes	Yes	Yes	Yes	Yes	No

Table 4: **The contribution of new director to board diversity conditional on board relative political stance.** The unit of observations is at the new director level, split into two types of boards for each firm-year observation i, t based on the number of Democratic-leaning $D_{i,t}$ and Republican-leaning $R_{i,t}$ directors except the new director. Panel A measures boards with a majority of Republican-leaning directors, indicated by $D_{i,t} < R_{i,t}$, while Panel B focuses on boards where Democratic-leaning directors are predominant, as $R_{i,t} < D_{i,t}$. The dependent variables reflect changes in five diversity dimensions resulting from the addition of new director. *Female* is the dummy variable of gender, where a value of one indicates female; *AAPI*, *Black*, and *Hispanic* are predicted ethnicity probability from ensemble method defined in 2.2.1. Firm control variables include firm age, board size, and market capitalization. The age of the new director is accounted for in the measures of Political Stance, Experience, and Skill. Standard errors, presented in parentheses, are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are standardized by subtracting the mean and dividing by the standard deviation.

	ΔPolitical Stance Diversity (1)	ΔExperience Diversity (2)	ΔSkill Diversity (3)	ΔEducation Diversity (4)	ΔInstitution Diversity (5)	ΔAge Diversity (6)
Panel A: Republican leaning						
Female	0.188***	0.198***	0.275***	-0.0738***	0.118***	0.0220***
	(0.0218)	(0.0177)	(0.0183)	(0.0175)	(0.0171)	(0.00626)
Black	0.0946***	0.0262***	0.0586***	-0.0179**	0.0208***	0.00378
	(0.0102)	(0.00694)	(0.00774)	(0.00732)	(0.00644)	(0.00240)
AAPI	0.0308***	0.0601***	0.0332***	0.0254***	-0.00304	0.0253***
	(0.0108)	(0.00958)	(0.00990)	(0.00842)	(0.00834)	(0.00357)
Hispanic	0.0147*	0.0594***	0.0264***	0.0115	0.0222***	0.00714***
	(0.00852)	(0.00831)	(0.00884)	(0.00750)	(0.00636)	(0.00241)
Observations	14,738	16,844	16,844	16,812	16,844	16,844
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Democratic leaning						
Female	-0.151***	0.205***	0.264***	-0.0552***	0.151***	0.00736
	(0.0192)	(0.0200)	(0.0200)	(0.0195)	(0.0192)	(0.00639)
Black	-0.0630***	0.0544***	0.0402***	-0.0218***	0.0157**	0.00656**
	(0.00636)	(0.00805)	(0.00786)	(0.00729)	(0.00745)	(0.00259)
AAPI	-0.0346***	0.0279***	0.0190**	-0.00653	0.0115	0.0236***
	(0.00682)	(0.00862)	(0.00786)	(0.00827)	(0.00912)	(0.00316)
Hispanic	-0.00392	0.0418***	0.00997	0.00803	0.00265	0.00240
	(0.00852)	(0.00917)	(0.00819)	(0.00850)	(0.00740)	(0.00250)
Observations	10,669	12,328	12,328	12,312	12,328	12,328
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: **New directors as political minority to board diversity: Democratic and Republican firms.** The unit of observation is at the level of new directors. The dependent variable, *Political Minority Dummy*, is defined for new directors based on whether their political stance (REP/DEM) is contrary to the board's prevailing political leaning (REP/DEM) at the time of their appointment. *DemMaj* is a dummy variable indicating a firm's political leaning, with one representing Democratic leaning and zero indicating Republican leaning. *Female* is the dummy variable for gender, where a value of one indicates female. *AAPI*, *Black*, and *Hispanic* represent the predicted probabilities of ethnicity, derived from an ensemble method as defined in 2.2.1. Their interactions with the dummy variable *DemMaj* are included in columns (2), (3), and (4). Firm controls, including firm size, board size, and firm age, are incorporated but not reported for columns (3) and (4). Column (4) additionally includes five firm-year diversity measure controls: Experience (BERT), Experience (TF-IDF), Skill, Age, and Political Stance. Standard errors, enclosed in parentheses, are clustered at the firm level. Significance levels are denoted as *, **, and *** for the 10%, 5%, and 1% levels, respectively. All variables are standardized by subtracting the mean and dividing by the standard deviation.

	Political Minority Dummy			
	(1)	(2)	(3)	(4)
Female	0.0480***	0.216***	0.214***	0.164***
	(0.0101)	(0.0124)	(0.0124)	(0.0111)
Black	0.00102	0.0728***	0.0724***	0.0488***
	(0.00408)	(0.00442)	(0.00444)	(0.00411)
AAPI	-0.00294	0.0480***	0.0478***	0.0249***
	(0.00495)	(0.00655)	(0.00657)	(0.00623)
Hispanic	0.00323	0.0103*	0.0102*	-0.0000528
	(0.00449)	(0.00607)	(0.00610)	(0.00547)
DemMaj	-0.0143	0.0844***	0.0834***	0.0447***
	(0.00963)	(0.0107)	(0.0108)	(0.00906)
Female × DemMaj		-0.362***	-0.363***	-0.260***
		(0.0187)	(0.0188)	(0.0168)
Black × DemMaj		-0.152***	-0.152***	-0.106***
		(0.00668)	(0.00670)	(0.00614)
AAPI × DemMaj		-0.0933***	-0.0922***	-0.0489***
		(0.00885)	(0.00888)	(0.00801)
Hispanic × DemMaj		-0.0170*	-0.0174*	-0.00391
		(0.00886)	(0.00889)	(0.00774)
Observations	14,590	14,590	14,496	14,200
Industry FE	Yes	Yes	Yes	Yes
Firm Controls	No	No	Yes	Yes
Diversity Controls	No	No	No	Yes

Table 6: **The contribution of new director to board diversity: Democratic and Republican states and firms.** The unit of observation is at the level of new directors, categorized based on the political stances of the board and the states of the firms' headquarters as obtained from Compustat. The classification of a *Rep/Dem state* is determined according to the presidential election results, which can be referenced at U.S. President 1976–2020 - U.S. Presidential Elections, with the election result being forward filled for the subsequent three years. The dependent variable measures the change in political diversity resulting from the addition of a new director. *Female* is the dummy variable for gender, with a value of one indicating female; *AAPI*, *Black*, and *Hispanic* represent the predicted probabilities of ethnicity, derived from an ensemble method as defined in 2.2.1. Firm control variables, including firm age, board size, market capitalization, and directors' age, are controlled for in each column. Columns (1) to (4) are double sorted based on *State* and *firm leaning*, while columns (5) to (8) are solely sorted based on *firm leaning*, with additional controls for Dem% (representing the state-year percentage of Democratic executives) and Dem%(non-White Male) (for non-White-Male executives). Standard errors, enclosed in parentheses, are clustered at the firm level. Significance levels are denoted as *, **, and *** for the 10%, 5%, and 1% levels, respectively. All variables are standardized by subtracting the mean and dividing by the standard deviation.

	ΔPolitical Stance Diversity							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Female	0.183***	-0.132***	0.184***	-0.155***	0.173***	-0.151***	0.171***	-0.148***
	(0.0320)	(0.0460)	(0.0301)	(0.0213)	(0.0242)	(0.0253)	(0.0239)	(0.0254)
Black	0.0892***	-0.0591***	0.104***	-0.0639***	0.0706***	-0.0588***	0.0732***	-0.0600***
	(0.0143)	(0.0143)	(0.0146)	(0.00744)	(0.0112)	(0.00936)	(0.0111)	(0.00938)
AAPI	0.00970	-0.0530***	0.0402***	-0.0288***	0.0287**	-0.0365***	0.0284**	-0.0367***
	(0.0158)	(0.0170)	(0.0146)	(0.00747)	(0.0126)	(0.00880)	(0.0125)	(0.00883)
Hispanic	0.0191	-0.0253*	0.00994	0.00276	0.00841	0.00808	0.00794	0.00768
	(0.0139)	(0.0134)	(0.0108)	(0.0103)	(0.00905)	(0.0108)	(0.00896)	(0.0108)
%DEM(Non-White-Male)					0.0189**	-0.0000516		
					(0.00856)	(0.0128)		
%DEM							0.0175*	-0.00939
							(0.00954)	(0.0120)
Observations	6,712	2,557	7,998	8,074	11,771	7,487	11,984	7,518
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State	Rep	Rep	Dem	Dem	all	all	all	all
Firm Leaning	Rep	Dem	Rep	Dem	Rep	Dem	Rep	Dem

Table 7: **The contribution of new director to board diversity: Democratic and Republican firms.** The unit of observation is at the level of new directors. The dependent variable assesses the change in political diversity resulting from the addition of a new director. *Female* is the dummy variable for gender, with a value of one indicating female; *AAPI*, *Black*, and *Hispanic* denote the predicted probabilities of ethnicity, derived from an ensemble method as outlined in 2.2.1. Firm control variables, such as firm age, board size, market capitalization, and directors' age, are accounted for in each column. Columns (1) and (2) are sorted based on *firm leaning*, while columns (3) to (5) include the entire sample with interaction terms involving the firm's political leaning dummy *DemMaj*, and additional controls for Dem% (representing the state-year percentage of Democratic executives) and Dem%(Non-white Male) (pertaining to non-white male executives). Standard errors, presented in parentheses, are clustered at the firm level. Significance levels are indicated by *, **, and *** for the 10%, 5%, and 1% levels, respectively. All variables are standardized by subtracting the mean and dividing by the standard deviation.

	ΔPolitical Stance Diversity				
	(1)	(2)	(3)	(4)	(5)
Female	0.174***	-0.152***	0.178***	0.176***	0.178***
	(0.0242)	(0.0254)	(0.0241)	(0.0238)	(0.0241)
Black	0.0707***	-0.0592***	0.0702***	0.0729***	0.0703***
	(0.0112)	(0.00938)	(0.0111)	(0.0110)	(0.0111)
AAPI	0.0285**	-0.0362***	0.0307**	0.0302**	0.0304**
	(0.0126)	(0.00884)	(0.0125)	(0.0124)	(0.0125)
Hispanic	0.00827	0.00799	0.00920	0.00904	0.00911
	(0.00905)	(0.0108)	(0.00907)	(0.00899)	(0.00907)
Age	0.00780	0.0417***	0.0205***	0.0210***	0.0204***
	(0.00952)	(0.0115)	(0.00705)	(0.00700)	(0.00705)
%DEM	0.0125	-0.0201		0.0171*	0.0106
	(0.0123)	(0.0157)		(0.00903)	(0.0116)
%DEM(Non-White-Male)	0.0130	0.0132	0.0202**		0.0148
	(0.0105)	(0.0166)	(0.00828)		(0.0102)
DemMaj			0.0487***	0.0497***	0.0512***
			(0.0167)	(0.0169)	(0.0170)
Female×DemMaj			-0.329***	-0.325***	-0.330***
			(0.0343)	(0.0343)	(0.0344)
Black×DemMaj			-0.130***	-0.134***	-0.130***
			(0.0141)	(0.0140)	(0.0141)
AAPI×DemMaj			-0.0703***	-0.0698***	-0.0695***
			(0.0150)	(0.0149)	(0.0150)
Hispanic×DemMaj			-0.00264	-0.00292	-0.00264
			(0.0142)	(0.0142)	(0.0142)
%DEM×DemMaj				-0.0244*	-0.0315*
				(0.0141)	(0.0187)
%DEM(Non-White-Male)×DemMaj			-0.0168		0.00346
			(0.0143)		(0.0187)
Observations	11,771	7,487	19,284	19,528	19,284
Industry FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Firm Leaning	Rep	Dem	All	All	All

Table 8: **Multinomial Logistic Regression analysis of Director Departures.** The unit of observation in this study is at the director-year level, and the base outcome category is defined as a director maintaining their position on the board. Departing to better positions categorizes directors who either join a new firm with at least a 25% larger market cap than their current firm or receive a clear promotion at the new firm within two years, while departing to lesser positions are those who experience demotion within two years at a new firm. No-information departures do not clearly fit into either category. *Female* is the dummy variable for gender, where a value of one indicates female. *AAPI*, *Black*, and *Hispanic* represent the predicted probabilities of ethnicity, derived from an ensemble method as detailed in 2.2.1. Firm controls include firm age, board size, and market capitalization. Five firm-year diversity controls—*Political Stance Diversity*, *Experience Diversity*, *Skill Diversity*, *Institutional Diversity* (*Inst Diversity*), and *Educational Diversity* (*Edu Diversity*)-are incorporated for regression (2). Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

	(1)			**(2)**		
	Better Positions	No Information	Lesser Positions	Better Positions	No Information	Lesser Positions
Female	1.086**	0.742***	0.150***	1.101**	0.716***	0.155***
	(0.0439)	(0.0150)	(0.0335)	(0.0455)	(0.0147)	(0.0350)
Black	1.226***	1.047*	0.431***	1.248***	1.017	0.425***
	(0.0836)	(0.0287)	(0.0933)	(0.0855)	(0.0284)	(0.0934)
AAPI	1.106	1.320***	0.870	1.079	1.328***	0.820
	(0.0846)	(0.0575)	(0.186)	(0.0874)	(0.0579)	(0.187)
Hispanic	1.087	1.032	0.519**	1.061	0.946	0.515**
	(0.117)	(0.0512)	(0.160)	(0.117)	(0.0443)	(0.165)
Age	0.964***	1.046***	0.969***	0.965***	1.046***	0.969***
	(0.00162)	(0.00129)	(0.00332)	(0.00168)	(0.00134)	(0.00347)
ΔExperience Diversity				1.151***	1.183***	1.056
				(0.0181)	(0.00919)	(0.0452)
ΔPolitical Stance Diversity				1.008	1.004	0.925
				(0.0141)	(0.00598)	(0.0459)
ΔSkill Diversity				0.932***	1.049***	1.025
				0.0144)	(0.00669)	(0.0440)
ΔInstitution Diversity				0.931***	0.956***	0.777***
				(0.0153)	(0.00707)	(0.0334)
ΔEducation Diversity				1.034**	1.015**	1.044
				(0.0154)	(0.00640)	(0.0440)
Observations	471,133	471,133	471,133	449,558	449,558	449,558
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm Control	Yes	Yes	Yes	Yes	Yes	Yes

Table 9: **Stock performance during Covid pandemic.** Panel A reports estimates of cross-sectional regressions of industry-adjusted returns on board characteristics and diversity measures. Industry-adjusted returns are calculated as, where we use the SIC three-digit clasification to define industry affiliation. Panel B reports estimates of characteristics-adjusted returns on same board characteristics. Characteristics-adjusted returns are calculated using Daniel et al. (1997) approach. All board characteristics are defined in Table A1. Returns are winorized at the 1% and 99% levels. Significance levels are denoted by *, **, and *** for the 10%, 5%, and 1% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Industry-Adjusted Excess Return						
Gender Diversity	-0.0718***				-0.0693***	-0.0670***
	(0.0198)				(0.0211)	(0.0216)
Racial Diversity	0.0354**				0.0400***	0.0345**
	(0.0149)				(0.0153)	(0.0153)
Experience Diversity		0.128***			0.127***	0.136***
		(0.0293)			(0.0304)	(0.0307)
Skill Diversity		0.0437***			0.0549***	0.0485***
		(0.0161)			(0.0163)	(0.0164)
Age Diversity			-9.24e-05		-0.00244	-0.00160
			(0.00279)		(0.00279)	(0.00288)
Political Stance Diversity			0.0122		0.0103	0.0117
			(0.00989)		(0.00985)	(0.00986)
Education Diversity				-0.0461***	-0.0476***	-0.0494***
				(0.0130)	(0.0131)	(0.0132)
Institution Diversity				0.0112	0.00736	0.00432
				(0.0124)	(0.0131)	(0.0131)
Technology skill						0.0440***
						(0.0133)
Age below 50 Female						-0.0311
						(0.0566)
Market Cap	0.0122***	0.0107***	0.0108***	0.0103***	0.0130***	0.0126***
	(0.00130)	(0.00121)	(0.00126)	(0.00122)	(0.00137)	(0.00138)
Constant	-0.128***	-0.218***	-0.136***	-0.109***	-0.216***	-0.216***
	(0.0102)	(0.0196)	(0.0123)	(0.0144)	(0.0236)	(0.0237)
Observations	3,065	3,065	2,911	3,060	2,910	2,910
R-squared	0.030	0.033	0.026	0.028	0.047	0.050

Table 9, continued.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: DGTW (size, BM, Mem, and liquidity) adjusted return						
Gender Diversity	-0.0258				-0.0160	-0.0201
	(0.0213)				(0.0224)	(0.0231)
Racial Diversity	0.0219				0.0269*	0.0242
	(0.0159)				(0.0161)	(0.0161)
Experience Diversity		0.0771**			0.0815**	0.0864**
		(0.0343)			(0.0345)	(0.0347)
Skill Diversity		0.0247			0.0368**	0.0352**
		(0.0173)			(0.0179)	(0.0179)
Age Diversity			0.00195		0.00111	0.00103
			(0.00299)		(0.00304)	(0.00316)
Political Stance Diversity			-0.00826		-0.00726	-0.00615
			(0.0102)		(0.0102)	(0.0102)
Education Diversity				-0.0165	-0.00879	-0.00959
				(0.0136)	(0.0139)	(0.0138)
Institution Diversity				0.0195	0.0230*	0.0217
				(0.0132)	(0.0136)	(0.0136)
Technology skill						0.0376**
						(0.0177)
Age below 50 Female						0.0112
						(0.0557)
Market Cap	0.00177	0.00155	0.00121	0.00112	0.00187	0.00169
	(0.00147)	(0.00139)	(0.00145)	(0.00139)	(0.00154)	(0.00154)
Constant	-0.0156	-0.0696***	-0.00994	-0.0193	-0.0942***	-0.0972***
	(0.0113)	(0.0224)	(0.0134)	(0.0162)	(0.0267)	(0.0267)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,414	2,414	2,297	2,410	2,296	2,296
R-squared	0.256	0.258	0.263	0.256	0.27	0.272

Appendix A. Variable Definition

Table A1: **Variable Descriptions.**

Dependent Variable	Descriptions
Firm level	
Experience(BERT) Diversity	Diversity based on textual bios of board directors. Computed as one minus the average cosine similarity of Sentence-BERT model representation of textual bios.
Experience(TF-IDF) Diversity	Diversity based on textual bios of board directors. Computed as one minus the average cosine similarity of the TF-IDF representation of textual bios.
Skill Diversity	Diversity based on the two most prominent skills of board directors. Computed as one minus the average cosine similarity of skill representations
Political Stance Diversity	One minus the adjusted HHI(Herfindahl–Hirschman Index) of political stances among board directors. Computed as $1 - \frac{\left[N_{i,t} \times \left(P_D^2 + (1-P_D)^2\right) - 1\right]}{N_{i,t}-1}$ where $P_D = \frac{D_{i,t}}{D_{i,t}+R_{i,t}}$, and $D_{i,t}$ and $R_{i,t}$ refer to the number of Democratic and Republican-leaning directors for the i, t firm-year observation, respectively, and $N_{i,t}$ is the sum of the two.
Racial diversity	Diversity in four ethnicities: AAPI, Black, Hispanic, and White. Calculated as $1 - P_{\text{AAPI}}^2 - P_{\text{Black}}^2 - P_{\text{Hispanic}}^2 - (1 - P_{\text{AAPI}} - P_{\text{Black}} - P_{\text{Hispanic}})^2$ where $P_{\text{AAPI}}, P_{\text{Black}}, P_{\text{Hispanic}}$ refers to the shares of directors of AAPI, Black, and Hispanic origin.
Age Diversity	Scaled standard deviation of the board directors' ages, age diversity$_{i,t}$ = $\frac{1}{3}\sqrt{\frac{1}{k_i-1}\sum_{j=1}^{k_i}\left(\text{age}_{i,j,t} - \overline{\text{age}}_{i,t}\right)^2} - 2.4$ for firm i at time t consisting of k_i directors from $j = 1, \ldots, k_i$.
Gender Diversity	Diversity in binary genders of directors. Computed as $1 - P_f^2 - (1 - P_f)^2$, where P_f refers to the share of female directors.
Individual director level	
ΔExperience(BERT) Diversity	Change in experience(BERT) Diversity resulting from the addition of a new director. Computed as the difference between the current board's BERT experience diversity and the counterfactual board without this director.
ΔExperience(TF-IDF) Diversity	Change in experience(TF-IDF) Diversity resulting from the addition of a new director. Computed as the difference between the current board's TF-IDF experience diversity and the counterfactual board without this director.
ΔSkill Diversity	Change in Skill Diversity resulting from the addition of a new director. Computed as the difference between the current board's skill diversity and the counterfactual board without this director.
ΔRacial Diversity	Change in Racial Diversity resulting from the addition of a new director. Computed as the difference between the current board's racial diversity and the counterfactual board without this director.
ΔAge Diversity	Change in Age Diversity resulting from the addition of a new director. Computed as the difference between the current board's age diversity and the counterfactual board without this director.
Political Minority Dummy	An indicator equal to one if the political stance of new directors (REP / DEM) is contrary to the board's prevailing political leaning (REP/DEM) at the time of his/her appointment.

Internet Appendices for
"A Diverse View on Board Diversity"

IA. Technical Details in the Construction of Diversity Measures

IA.1. Algorithmic Optimization of Race Classification

To optimize our model, we fine-tune it by minimizing the cross-entropy loss. Mathematically, the loss function for the one-dimensional cross-entropy is defined as $-\Sigma_i\, y_i\, log(\hat{y}_i)$, where y_i is the truth, while $\hat{y}_i$ is the predicted probability. Entropy loss gauges the discrepancy between the predicted probability distribution and the actual outcomes in the training data. To facilitate this, we divided all directors with identified ethnicities into two parts: a training set with 67% of the data and an out-of-sample test set that makes up the remaining 33%. Within the training set, we adopt a five-fold cross-validation approach. This means that the training data is further divided into five subsets. In each iteration of the validation process, the model is trained on four of these subsets and validated on the fifth. This procedure is repeated five times, ensuring that each subset serves as the validation set once. The ensemble then assigns ethnicity based on the highest predicted probabilities among the AAPI, Black, Hispanic and White categories. Note that the training sample is predominantly White such that simply classifying any director as White would yield an 84% accuracy. Therefore, we further check that the accuracy to predict non-White is 80%, significantly higher than the recall, or the true positive rate of 69%. This suggests that our ensemble estimator is especially robust against Type I errors for ethnic minorities.

IA.2. Retrieval of Director Bios from EDGAR

We retrieve director bios from the proxy statement (DEF 14A filing) via SEC EDGAR index, when needed, in a two-step procedure. In the first step, we collect all paragraphs that contain the director's name. In the second step, we identify the clusters of paragraphs that represent textual bios using the Sentence BERT model. Because director bios in Equilar are from multiple sources (and not exclusively from the proxy statement), we resort to the Refinitive ESG Board Member Data as our training data, as its textual bios are extracted directly from DEF 14A.

The second step consists of both the in-sample training and the out-of-sample test. First, we use the pre-trained Sentence BERT model to measure the similarity between each name-containing paragraph and the actual bios, and record the closest-matched paragraph for each firm-year-director. The resulting training set contains 75,962 textual paragraphs, of which 24% were the actual bios. Second, we then partition this dataset into three parts: 60% for in-sample training, 20% for validation, and the final 20% for out-of-sample testing. In our fine-tuning phase, we adopted a batch size of 16 and trained over 10 epochs, aiming to reduce cross-entropy loss. Finally, in the out-of-sample evaluation, our Sentence BERT classifier achieved 85% accuracy in classifying the director bios within DEF 14A filings.

IA.3. Skill Keywords

Skill	Key Words
Leadership	CEO, Chief Executive Officer
Law	Law, Legal, JD, Counsel, Attorney, Court, Litigation, Compliance, Lawyer, Antitrust law, Intellectual property, Labor law, Patent lawyer, International lawyer, LLM, Contract law, Bankruptcy law, Securities law, Civil law, JSD, Criminal law, Juris Doctor, Counseller
Marketing	Advertising, A/B testing, Branding, Consumer, Market funnel, Advertisement, Conversion rate, Marketing, B2B, B2C, C2B, C2C, Cross selling, Demand generation, Key performance indicators, Mark-up, Pipeline management, Sales pipeline, Customer relationship management
Finance/Accounting	Financial foundation, Banking, Chief financial officer, CFO, Capital structure, Investment, Capital markets, Real estate, Risk management, Sales and Trading, Treasury, Corporate finance, CPA, Accounting, Deloitte, Ernst & Young, Audit, KPMG, PWC, Financial statement, Accountant, Finance experience, M&A, Venture capital, Private Equity, Mergers and acquisitions, Financial background, Financial expert, Financial experience, Financial management, Understanding of finance, Finance experience, Auditing
Technology	Automation, CIO, Web 3, Telecommunication, Blockchain, Electronics, Chief information officer, R&D, Hardware, Technological, Innovation, Laboratory, Software developer, Semiconductor, Research and development, Software, Technical, Software engineer, IT infrastructure, Integration testing, Cybersecurity, Disruptive innovation, Electronics, Invention, Web 2, Information technology, Software as a service product, Saas, Cloud computing, CTO, Chief technology officer
Academics	Academy, Chancellor, Dean, Author, Faculty, PhD, Professor, Provost, Academic , Tenured, Tenure track, Lecturer, Instructor, Teaching fellow, Prof., Academia, Academic, Academia
Operation	Chief operating officer, COO, Supply chain, Warehouse management, Coaching, Coordination, Human resource, Procurement, Expansion and operation, HR, Logistics, Inventory management, Business planning, Decision making, Problem solving, Internal operation

Skill	Key Words
Regulation / Government	Government, Governor, Regulation, Cabinet, Regulatory, Military officer, U.S. Army, Armed forces, Department of State / Treasury / Labor / Agriculture / Defense / Justice / Homeland Security / Health and Human Services / Energy / Interior / Housing and Urban Development / Commerce / Education / Immigration Services / Transportation / Veterans Affairs, Attorney general, Secretary of State / Treasury / Labor / Agriculture / Defense / Justice / Homeland Security / Health and Human Services / Energy / Interior / Housing and Urban Development / Commerce / Education / Immigration Services / Transportation / Veterans Affairs, Director of national intelligence, Trade Representative, Director of the office of management and budget, Director of the office of science and technology policy, Administrator of the environmental protection agency, Administrator of the small business administration, Government and regulation, Regulatory

IA.4. Classification of political stance with FEC data

In the first step, we aggregate FEC individual contributions to federally registered political committees at the contributor level. This aggregation is based on first name, middle name, last name, occupation, employer, and address, thus creating a biannual FEC contributor dataset. In the second step, we match board directors with this individual contributors dataset using first and last names. We specifically exclude contributions from four occupations: air traffic controllers, firefighters, airline pilots, and farmers.

If a director is matched with multiple contributors, we apply two distinct filters based on employers and addresses. We first compare the employer of each contributor with the director's employment history recorded in BoardEx. We retain matches where the fuzzy employer name similarity score is greater than 78. Second, we remove any matches where the contributor's address is more than 100 miles from any of the headquarters of the director's employment history. After applying two filters, we aggregated the political contributions for each director-contributor-year combination. In cases where a director is still matched with multiple contributors, we select the one with the highest total political contributions.

To categorize these contributions by political affiliation, we integrate FEC committee data with information from Super PAC, Leadership PAC and Carey PAC, using records from OpenSecret that span 2002 to 2020. This process allows us to assign each committee to a specific political affiliation (Democratic, Republican, Other, and Unaffiliated). Among the 43.6% committees that are classified as nonbipartisan, about 17.9% of the committees have a third-party affiliation, which we classify as "Others." The rest are committees without clear affiliations, which we label as "Unaffiliated." Finally, we sum up the contributions from 2002 to 2020 under these four political affiliations for each director. The director's political stance is then determined by the political affiliation that has the highest cumulative contribution.

IB. Supplementary Results

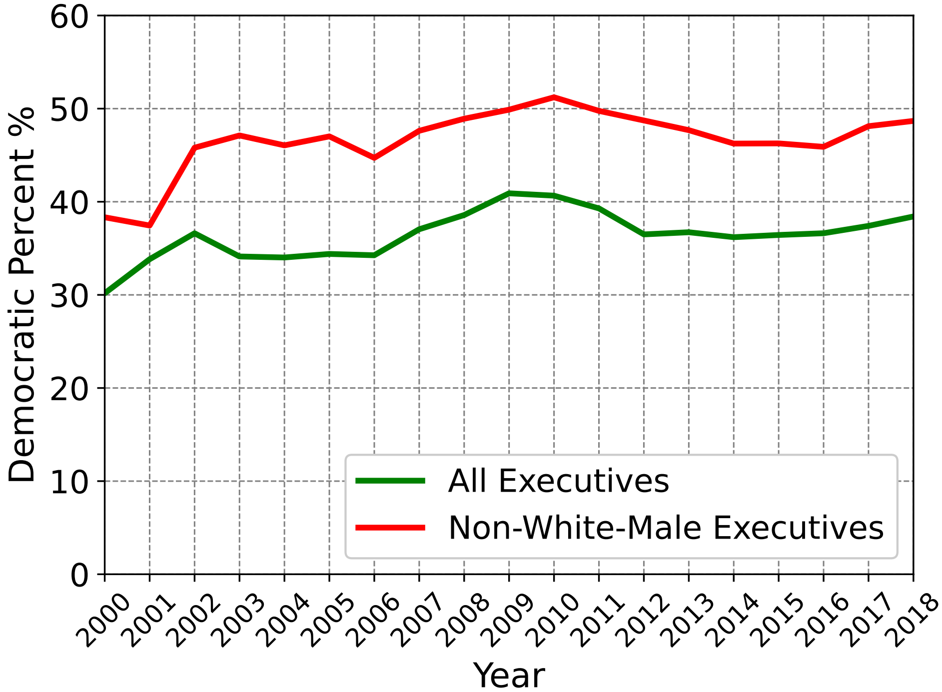


Figure IB.1: Time Series of the proportion of Executives on Execucomp with Democratic-Leaning view based on political contributions.

Table IB.1: **The contribution of new director to board diversity conditional on board expansions and replacements.** The unit of observations is at the new director level, split into two types of boards: Panel A measures boards that have an equal number of incoming and departing directors, while Panel B focuses on boards where the number of new directors exceeds that of the departing directors. The dependent variables reflect changes in five diversity dimensions resulting from the addition of new director. *Female* is the dummy variable of gender, where a value of one indicates female; *AAPI*, *Black*, and *Hispanic* are predicted ethnicity probability from ensemble method defined in 2.2.1. Firm control variables include firm age, board size, and market capitalization. The age of the new director is accounted for in the measures of Political Stance, Experience, and Skill. Standard errors, presented in parentheses, are clustered at the firm level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. All variables are standardized by subtracting the mean and dividing by the standard deviation.

	ΔPolitical Stance Diversity (1)	ΔExperience Diversity (2)	ΔSkill Diversity (3)	ΔEducation Diversity (4)	ΔInstitution Diversity (5)	ΔAge Diversity (6)
Panel A: Board replacement						
Female	0.0173	0.191***	0.288***	-0.0938***	0.0934***	0.0138*
	(0.0233)	(0.0201)	(0.0210)	(0.0199)	(0.0208)	(0.00703)
Black	0.0199*	0.0380***	0.0638***	-0.0256***	-0.00367	0.00620**
	(0.0103)	(0.00833)	(0.00857)	(0.00777)	(0.00819)	(0.00285)
AAPI	-0.00258	0.0338***	0.0138	0.0213**	0.00121	0.0251***
	(0.00897)	(0.00977)	(0.00983)	(0.00938)	(0.00961)	(0.00363)
Hispanic	0.00516	0.0578***	0.0235***	0.0100	-0.00434	0.00814***
	(0.00953)	(0.00838)	(0.00858)	(0.00824)	(0.00667)	(0.00277)
Observations	12138	14548	14548	14516	14545	14548
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Board expansion						
Female	0.0168	0.197***	0.256***	-0.0470***	0.124***	0.0120**
	(0.0169)	(0.0155)	(0.0154)	(0.0147)	(0.0146)	(0.00506)
Black	0.0107	0.0441***	0.0404***	-0.0246***	0.00569	0.00483**
	(0.00724)	(0.00604)	(0.00626)	(0.00606)	(0.00567)	(0.00200)
AAPI	-0.00219	0.0365***	0.0321***	-0.00159	-0.00971	0.0229***
	(0.00754)	(0.00774)	(0.00670)	(0.00654)	(0.00671)	(0.00258)
Hispanic	0.00359	0.0413***	0.0153**	0.00825	0.00425	0.00155
	(0.00652)	(0.00670)	(0.00648)	(0.00585)	(0.00557)	(0.00184)
Observations	18721	21431	21431	21390	21429	21431
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes