Diversity Narrative and Equity in Firm Leadership*

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Abstract

We provide causal evidence that the narrative of diversity from the *New York Times* articles has nudged the corporations to choose female CEOs to be equitable in terms of gender of firm leadership. This channel is independent of the board gender diversity, which was mandated in 2017 in California and later repealed in 2022. Surprisingly, the diversity narrative channel fails to explain the election of Indian CEOs in several HiTech firms over the last few years. We argue that the election of Indian CEOs was motivated to create a favorable image of Tech firms to Indian and Chinese labor. We conclude that providing equity in firm leadership in terms of ethnic diversity is harder compared to gender diversity.

Key Words: Diversity, Equity, Female CEO, Tech firms, India

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1 Introduction

"Diversity, Equity, and Inclusion," a.k.a. DEI initiatives, have been undertaken by almost every corporation, including universities in the United States and beyond. Evidence shows that diversity and inclusion lead to better outcomes for consumers and corporations. However, providing a level playing field based on equity is more challenging. This is because not everyone has the same background, social status, and start to their career. In this paper, we quantify a mechanism of diversity narrative, which is general in scope, that leads to the election of female CEOs. We start with a comprehensive set of keywords related to diversity, equity, inclusion and justice.[1] Then, We create a diversity narrative measure by applying a state-of-the-art natural language processing tool called *word2vec* to develop a dynamic dictionary of diversity-related words and count the frequency of these words in the *New York Times (NYT)* news articles.

We note that the board gender diversity of corporations has also increased over our research time horizon from 2011-2019. Surprisingly, our diversity narrative channel is independent of the board's gender diversity channel. This provides equity, in terms of representation, to both male and female stakeholders or critical decision-makers.

Our argument is that news is a crucial source for capturing the market's attention. News content is tailored to its readership, as evidenced by previous studies (Case, Quigley, and Shiller (2005); Gentzkow and Shapiro (2010); Mullainathan and Shleifer (2005)), and is known to form and shape public opinion and the perspectives of corporations. Extracting diversity from news is especially important as it draws attention to issues of diversity and inclusion. Research has shown that people prefer news that confirms their beliefs, but are also willing to pay for news that broadens their perspectives (Mullainathan and Shleifer (2005)). This highlights the significant role that media can play in shaping public opinion and worldview.

Drawing on the insights of Shiller (2019) who draws on numerous excerpts from *The New York Times* (henceforth, *NYT*) to argue that narratives can undergo mutation and become robust outbreaks, we further examine the implications of this phenomenon. Through our

[1] Source: https://www.diversity.pitt.edu/education/diversity-equity-and-inclusion-glossary

analysis of *NYT* and a series of rigorous robustness tests, we aim to understand better how narratives shape and influence societal and economic trends. Our findings offer valuable insights into the mechanisms by which narratives are propagated and how they can take hold in the public consciousness, often leading to significant changes in behavior and policy. Ultimately, our work sheds light on the important role of media in shaping public discourse and offers a framework for future research in this area.

Our analysis of *New York Times* articles from 2010 to 2019 demonstrates that articles related to diversity have influenced how corporations perceive diversity and implement related policies. The election of female or ethnically diverse CEOs has had far-reaching consequences beyond optics. In the case of hi-tech firms, the appointment of Indian CEOs has attracted top talent from India and China who believe that the American dream is still alive. As such, they are more likely to join hi-tech firms with Indian CEOs than comparable firms, even when they may provide similar or higher compensation.

We first construct a news-based diversity index to investigate how the diversity narrative shapes corporate hiring decisions. We apply the *word2vec* model developed by Mikolov, Chen, Corrado, and Dean (2013) to develop a time-varying dictionary of *diversity* from around 1.5 million NYT articles from 2000 to 2020. We then use this dictionary to compute the frequency of diversity-related words in the NYT news articles from 2010 to 2019 to compute the daily diversity score. After controlling for common asset pricing factors, we then regress the firm daily stock returns on changes in this diversity index to construct our firm diversity exposures or diversity betas.

We explore the impact of this novel diversity narrative from NYT alongside board gender diversity which has been relatively well-studied. In Figure 4, it is evident that the relationship between the election of female CEO the board gender diversity becomes exponential from 2016 onwards. The yearly curves become steeper, and this exponential change occurs when the threshold of 40% for board gender diversity is breached. Essentially, a critical mass of gender diversity at the board level leads to an almost sure election of female CEO in the firm. We also visualize the evidence of this critical mass in a 3-dimensional diagram where the propensity of the election of female CEO is plotted against the board gender diversity and the ESG scores. We find similar evidence of an increase in the probability of the election of female CEO with increasing beta of diversity narrative. The effect is pronounced for 2017, which we later use for causal analysis. Interestingly, in Fig 6 and Fig 7, we see this relationship of female CEO with NYT diversity narrative whenever the absolute value of beta increases.

The first evidence of equity from this diversity narrative shows up in the compensation gaps between male and female CEOs over time. Figure 8 plots the differences in various compensation measures between male and female CEOs. From TDC1 and TDC2 plotted in the primary axis, we observe that the total compensation of male and female counterparts become more equitable from 2014-2019. In fact, the diversity narrative may have led to the election of female CEOs and slanted the female leadership ratio in firms. But because of search friction in finding equally capable and qualified female CEOS, the female CEOs may have had higher total compensation. However, over time, this slant has created equitable total compensation. Looking at the base salary and bonus in the secondary axis, we observe that the base salary is becoming more equitable across male and female CEOs. However, the bonus component of the compensation increases significantly for female CEOs. This points to an exciting mechanism of attaining equity in total compensation.

The literature on leadership regarding gender diversity has not reached a consensus. Schubert, Brown, Gysler, and Brachinger (1999) identify gender-specific opportunity sets as the primary driver of financial decisions rather than the stereotype that female managers and directors are most risk averse. Tate and Yang (2015) argue that women in leadership positions cultivate more female-friendly cultures inside their firms. On the other hand, Huang and Kisgen (2013a) document the overconfidence of male executives undertaking more acquisitions and issuing debt more often than female executives.

Diversity in decision-making processes facilitates consideration of a more comprehensive range of strategies (Dezső and Ross (2011))) and can lead to higher quality decision-making (Matsa and Miller (2013)). The election of a female CEO alleviates the supply-side constraints of search friction costs for local talented female executives imposed by the California Bill on September 2018 (Hwang, Shivdasani, and Simintzi (2018)). We find support for a 'critical mass theory' or 'gravitational pull theory' (see Adams and Funk (2012)) that board gender diversity leads to the almost sure election of a female CEO, beyond a threshold (see

Figure 4).

Economics and social psychology literature document that diversity in a team moderates group decisions (Sah and Stiglitz (1986); Sah and Stiglitz (1991); Moscovici and Zavalloni (1969)). In line with organizational behavior literature, which documents that diversity is multi-dimensional (see Phillips and O'Reilly (1998); Bernile, Bhagwat, and Yonker (2018)), we explore gender and ethnic diversity in firm leadership. We also control for other elements of diversity, such as, age, tenure as CEO, educational background, financial expertise, etc.

Borokhovich, Parrino, and Trapani (1996) documents a strong positive relationship between the percentage of outside directors and the frequency of outside CEO succession. The likelihood that an executive from outside the firm is appointed CEO increases monotonically with the percentage of outside directors. This monotonic relation is observed for both voluntary and forced departures. Evidence from stock returns around succession announcements indicates that, on average, shareholders benefit from outside appointments but are harmed when an insider replaces a fired CEO. To rule out the above *board independence channel*, we control for *bindep* variables in our specifications, and our results still hold.

Personal characteristics of board members, such as age, education, and professional experience, are also likely to directly affect a director's ability to monitor and advise. The impact on firm performance can be ascribed, among other things, to a monitoring channel: female directors are likely to exert more substantial monitoring efforts than their male counterparts (see Cardillo, Onali, and Torluccio (2020)), which might increase performance for firms with weak governance mechanisms (Adams and Ferreira (2009)). The overconfidence channel is explored in Huang and Kisgen (2013b). However, we do not find evidence of the *monitoring channel* from board gender diversity, as corroborated by the non-significant self-reported governance (G score) channel from the ESG score.

Cooper (2017) supports the stakeholder theory of CSR and does not support the entrenchment theory. It is the first study to look at CSR, CEO turnover, and gender issues concurrently. The findings suggest that CSR is acting as a deterrent to bad behavior by executives (CEO) in the face of weak financial performance. Y. Li, Gong, Zhang, and Koh (2017) report that higher CEO power enhances the ESG disclosure effect on firm value, indicating that stakeholders associate ESG disclosure from firms with higher CEO power with a more outstanding commitment to ESG practice.

Shivdasani and Yermack (1999) study whether CEO involvement in the selection of new directors influences the quality of appointments to the board. When the CEO serves on the nominating committee or no nominating committee exists, firms appoint fewer independent outside directors and more questionable outsiders with conflicts of interest. The evidence may illuminate a mechanism CEOs use to reduce pressure from active monitoring.

- *Hypothesis 1:* Firms that cater to the diversity narrative are more likely to elect female CEOs to make firm leadership equitable.
- *Hypothesis 2:* HiTech firms have less propensity to elect female CEOs.
- *Hypothesis 3:* HiTech firms elect CEOs with ethnic diversity, namely Indian CEOs.

We will provide evidence for each hypothesis.

2 Firm Exposures to News-Based Diversity Narrative

In this section, we discuss the construction of our firm diversity exposures. We first discuss the data source, then the construction of our news-based diversity index, and finally, firm exposures to this diversity index.

2.1 News Data

We construct the index of diversity attention discussed in the NYT articles. We choose the NYT as it is one of the most prestigious and widely circulated worldwide and has been used in finance research such as Garcia (2013) and Hillert and Ungeheuer (2019). From the archive of all NYT articles from 2000 to 2020, we remove articles having fewer than 100 content words to reduce noises introduced by these short articles. Other than this restriction, we keep all articles in all columns and sections of the NYT since we want to study the proportion of NYT content related to diversity. This serves as a good approximation of public attention to diversity. Our final news sample consists of around 1.5 million news articles having an average of 400 words per article.

We start our sample in 2010 because, as discussed in the following subsection, we estimate our model using *word2vec* on a rolling 120-month basis to construct the time-varying dictionary of diversity. To prepare texts for *word2vec*, we remove one-letter words, tags, and special characters and perform lemmatization (i.e., remove word endings such as *es* and *ing* and revert words to roots such as *was* $\rightarrow$ *be*). We do not remove stop words because *word2vec* needs the context of a word to learn its numeric representation.

2.2 Construction of News-Based Diversity Index

We apply an advanced word embedding method called *word2vec* developed by Mikolov et al. (2013) to construct the real-time diversity score. *word2vec* has seen huge popularity and adoption in various fields. In finance, *word2vec* has been used to construct dictionaries of corporate culture (K. Li, Mai, Shen, & Yan, 2021) or macroeconomics (van Binsbergen, Bryzgalova, Mukhopadhyay, & Sharma, 2022). In essence, *word2vec* is an unsupervised word embedding model to construct vector representations for words in a document. It does so by training a neural network to predict the probability of a word given its neighbor words. Thus, *word2vec* is a contextualized NLP method as compared to the traditional bag-of-word approach that treats words in isolation.

We differ from the previous applications of *word2vec* in finance by applying it to develop a time-varying dictionary of diversity. More specifically, as illustrated in Figure 1, every month t, we use the past 120 months (including the current month) of news data to train the *word2vec* model.[2]

The input of *word2vec* is the collection of all sentences belonging to the news articles in the 120-month training window. Each sentence comprises of one-word terms (unigrams) and two-word terms (bigrams). Instead of arbitrarily combining individual words into bigrams, we adopt the automatic standard phrase detection method introduced by Mikolov et al. (2013). Specifically, this method combines two unigrams into one bigram if these words commonly occur together. In our training, we combine two words into a bigram if they occur next

[2] We use the `gensism` package in `Python` to train the *word2vec* model. In training, as recommended by the package author, we use a window size of five words and keep words with at least five appearances in the corpus.

to each other at least five times in the training news collection. For example, the sentence "Corporate governance is an important field." is converted into "corporate_governance is an important field" where *corporate_governance* is treated as one word by *word2vec*. The advantage of combining words into bigrams is twofold. First, it helps the model construct vector representations for sensible words. Second, it reduces the number of words that the model is required to learn, thus speeding up the training process.

The output of the monthly estimation process is one numeric vector for each word in the news collection. Following standard practice, we represent each word by a 100×1 vector. We have a numeric vector to represent the term diversity among these produced word vectors. Using these word vectors, we then compute the cosine similarity between all other terms in the news collection with *diversity*. We can then identify the 100 words having the highest cosine similarities with *diversity*, i.e., the 100 words most related to *diversity*. We refer to these 100 diversity-related words as the diversity dictionary in month t.

After constructing the diversity dictionary in month t, we compute the frequency of these diversity words in news articles in the next month $t + 1$. We sum up the total counts of these diversity-related words and divide them by the total number of words across articles each day in month $t + 1$ to compute the daily diversity attention scores in month $t + 1$.

We roll this estimation method one month forward by running the *word2vec* model in month $t+1$ using news data from month $t-119$ to month $t+1$ and computing the diversity score in month $t + 2$. Iterating this process forward, we can thus construct real-time daily news-based diversity attention.

In Figure 2, we plot the word cloud of our time-varying diversity dictionary, which aggregates our monthly 100-word dictionaries. In this word cloud, the bigger the terms, the higher the frequency of the words. We can see that all frequently used words are strongly related to diversity, such as *diversity, openness, equality, tolerance,* and *civic_engagement*.

In Figure 3, we plot the time series of our real-time diversity score from 2010 to 2020. Panel A plots the level daily index, and Panel B plots the change index. As mentioned above, the NYT began discussing AI in the mid-1980s.

2.3 Construction of Firm Exposures to News-Based Diversity

We use stock returns to compute firm exposures to our news-based diversity index available at the aggregate level. First, we compute the daily changes in our diversity index. Then, for each firm at the end of each year t, we regress its daily returns within that year onto the daily diversity change index and control for Fama and French (2018) six factors, including market (MKT), size (SMB), value (HML), momentum (MOM), profitability (RMW), and investment (CMA) as follows:

$$\begin{aligned} R^e_{i\tau_t} = \alpha_{it} + \beta^{div}_{it} Diversity_{\tau_t} + \beta^{MKT}_{it} MKT_{\tau_t} + \beta^{SMB}_{it} SMB_{\tau_t} + \beta^{HML}_{it} HML_{\tau_t} \\ + \beta^{MOM}_{it} MOM_{\tau_t} + \beta^{RMW}_{it} RMW_{\tau_t} + \beta^{CMA}_{it} CMA_{\tau_t} + \epsilon_{i\tau_t} \end{aligned} \tag{1}$$

where $R^e_{i\tau_t}$ is the excess return of stock i on day τ in year t and $\beta^{div}_{i,t}$ (referred to as *diversity beta*) is the variable of interest, capturing firm exposure to news-based diversity in year t after netting out common asset pricing sources of stock movements.

3 Data

We collect data about the gender of the directors and the proportion of female directors from BoardEx to create the variable *Gender diversity*, which is the number of female directors divided by the total number of directors on the board. From the same database, we also retrieve data on the number of independent directors on the board, the gender of the CEO, and whether the CEO is also the Chairman. We use these data to generate the variable *Board independence*, which is the ratio of the number of independent directors' dividends to the total number of directors, and *CEO duality*, which is a dummy variable equal to one if the CEO is also the Chairman and zero otherwise. We also control the board's size (total number of directors) with the variable *Board size*.

We use ExecuComp data to predict the race and ethnicity of CEOs of firms. Using *predictrace* package, we estimate the CEO's gender from her first name. Using the same package, we estimate the likely race of the CEOs using their last names. We also have information on the CEOs' salaries, bonuses, and total compensation. Salaries and bonuses are in thousands. The measures of total compensation, namely, TDC1 and TDC2 are also in thousands.

$$TDC1 = Salary + Bonus + Other + RestrictedStockGrants + LTIPPayouts + OptionGrants$$

$$TDC2 = Salary + Bonus + Other + RestrictedStockGrants + LTIPPayouts + OptionsExercised$$

Our paper introduces proprietary ESG data, which is a *consensus* score of around 200 ESG data sources globally, covering 30,000 public firms on a monthly basis. Many institutional investors expect corporations to manage ESG issues (Gibson, Krueger, Riand, and Schmidt (2019)) and monitor their holdings' ESG performance (Dyck, Lins, Roth, and Wagner (2019)) and end up using ESG scores provided by external agencies with serious conflicts of interest. Our paper de-biases any plausible collusion between the rater and ESG score recipient and alleviates the divergence (based on different scope, measurement, and weight of categories) of ESG ratings based on data from six prominent rating agencies - namely, KLD (MSCI Stats)[3], Sustainalytics[4], Vigeo Eiris (Moody's), RobecoSAM (SP Global), Asset4 (Refinitiv), and MSCI IVA, as documented by Berg, Kouml;lbel, and Rigobon (2019), e.g., the conflict of interest of Morningstar's view of a firm based Sustainalytics ESG score.

OWL Analytics offers ESG metrics designed to compare companies to their logical peer group and to identify which of our KPIs have been important financial factors for the companies in those peer groups. Peer groups can be designated by one of the three-factor pairs — Region and Industry, Region and Subsector, or Region and Sector. A company can belong to at most three peer groups. The purpose of dividing companies into peer groups is so we can isolate as many variables as possible affecting the financial performance of companies within those peer groups. Moreover, research has shown that not all ESG factors are as important to some industries and/or sectors as they are to others. In fact, some ESG factors have been shown to be positively material to some industries while simultaneously negatively material to other industries. As in all things, it is valuable to compare characteristics — whether

[3]KLD, formerly known as Kinder, Lydenberg, Domini & Co., was acquired by RiskMetrics in 2009. MSCI bought RiskMetrics in 2010. The data set was renamed to MSCI KLD Stats as a legacy database. The KLD data set does not contain an aggregate rating; it only provides binary indicators of "strengths" and "weaknesses". It is, however, frequently used in academic studies in aggregate form.

[4]Sustainalytics (with an ownership stake by Morningstar)

financial or sustainable — within the appropriate context.

ESG metrics are calculated based on the following rules:

- E1, E2, and E3 are averaged to create the Environment Score measured at 0–100.
- G1, G2, and G3 are averaged to create the Governance Score measured at 0–100.
- CIT1, CIT2, and CIT3 are averaged to create the Citizenship Score measured at 0–100.
- EMP1, EMP2, and EMP3 are averaged to create the Employer Score measured at 0–100.
- The Employer and Citizenship scores are averaged to create the Social Score measured at 0–100.
- Environment, Social, and Governance scores are averaged to create the overall ESG Score measured at 1–100.

We provide the summary statistics of the merged data from BoardEx, ExecuComp, and diversity exposures (i.e. betas) in Table 1. As is evident from the third quartile being zero, the number of female CEOs is clearly unbalanced compared to the historic and even current number of male CEOs. The diversity narrative score from NYT (b_d_diversity) is fairly symmetric. The board gender diversity (genderdiv) is variable between 0 and 1. We see around 6.8% firm-year observations from the tech industry. We also provide summaries of the mix of nationalities across board members, the number of executive and independent directors, the network size of the directors, and environment, social, governance, employment, and charity scores from OWL Analytics. As expected, we observe a right-skewed distribution for board independence. The age of CEOs is around 61.5 on average and is symmetric. There are 0.8% CEOs who hold the coveted CFA certification, possibly from Ivy League business schools. CPA is an easier more general public accounting certification for a CEO who generally rises up the ranks from an accounting background. There are around 2.3% of CEOs are PhDs, mostly in tech companies where technical expertise is a necessary criterion for being in firm leadership.

In Table 2, we summarize the merger with CEO ethnicity from ExecuComp. Clearly, the CEOs with coveted certifications of CFA, CPA, or the highest educational degree of a Ph.D. are non-white.

In Table 3, we test for the kurtosis of the data in Table 2. We find that if we only take the data beyond the first and third quartiles of the diversity narrative scores, we see the same percentage of CEOs with CFA, CPA, or Ph.D. This further corroborates our premise that firms that are prone to cater to the NYT diversity narrative happen to elect CEOs with hard evidence of education or certifications, which arguably is present mostly in non-white leaders.

In Tables 4 and 5, we document the average compensation measures of male and female CEOs across time, respectively. Overall, the trend is increasing however, the relative changes point us to a very interesting way of attaining equity in total compensation.

4 Methodology

We use a linear probability model with state and year-fixed effects to estimate the impact of the diversity narrative from NYT on the election of female CEOs.

$$Pr(Female\_n = 1|CEO) = \beta\_d * diversity\_narrative_{nt} + \beta\_g * board\_gender\_div_{nt}$$
$$\alpha * X_n + \gamma * Z_{nt} + \delta_s * S + \Psi_t * Y + \varepsilon$$

where $Female\_n$ for a firm n is the indicator variable that equals 1 if the firm elects a female CEO, and 0 otherwise. The diversity_narrative. X_n is time-invariant characteristics of CEOs, e.g., and of firms, e.g., whether the firm is in the tech industry, whether the CEO is also a board member, nationality mix of the board, number of executive and independent directors, network size, binary variable for board independence, education or certification of the CEOs, .loan and borrower characteristics (e.g., credit score and agency type). Z_{nt}: time-varying firm characteristics, e.g., firm size, CEO age, self-reported environmental, social, governance, employment, and charity scores for firms. S, Y are fixed effects for state and year.

5 Gender Diversity in Leadership

We use fixed effect linear probability models to estimate the impact of board gender diversity and the diversity narrative from *NYT* on the election of female, non-white, Asian, Indian, and Chinese CEOs.

In Table 6, Model 1 estimates the impact of both board gender diversity and the diversity narrative from *NYT* o on the election of female CEOs in the exact specification. As is evident, both these channels are statistically significant. Other than that, the nationality mix on the board negatively affects the election of female CEOs. This is because people of different nationalities perceive female leadership differently. Also, board independence leads to the election of female CEOs.

In Model 2 and Model 3, we find that separately board gender diversity and diversity narrative increase the propensity of the election of female CEOs, respectively. The marginal impact of board gender diversity and diversity narrative remains almost the same when used in the same specification in Model 1. Namely, the factor loading for board gender diversity changes from 0.4183 to 0.4184 between Model 1 and Model 2. Similarly, the coefficient of diversity narrative changes from 0.0016 to 0.0018 between Model 1 and Model 3.

In Models 4, 5, and 6, we conduct robustness checks for our results, including a dummy for tech industries. We provide evidence that tech firms have a 1.72% less propensity to elect female CEOs. The results remain robust after controlling CEO education in Table 7. This implies that the educational pedigree per se is not the reason for electing female CEOs. Highly desired business certifications like CFA and CPA reduce the likelihood of the election of female CEOs.

We add the dimension of size as the logarithm of assets. We avoid singularity at asset size zero by adding one to assets. In Table 8, our results are robust even after accounting for firm size, albeit slightly diminished in magnitude. These results hold after controlling for the most comprehensive set of possible explanatory variables that may explain the election of female CEOs in firms. The direction of the coefficients for all other control variables is still consistent.

These results provide evidence of the impact of the diversity narrative on the election of gender diversity in firm leadership. In the next section, we show the causal results of the diversity narrative leading to the election of female CEOs.

6 California Bill: Gender Diversity and Board Quotas

Senate Bill 862 was introduced in the California legislature in January 2018 by two Democratic state senators, Hannah-Beth Jackson, and Toni Atkins, to improve gender diversity on corporate boards.[5] However, opponents of the bill, e.g., the California Chamber of Commerce and others have argued that the composition of corporate boards is a prerogative of firms and should not be mandated by the government. The bill was passed by the House on May 31, 2018. and then introduced in the California Senate where it passed on August 29, 2018. The bill was approved and signed into law by Governor Jerry Brown on Sunday, September 30, 2018. The passage of the law received widespread media attention on Monday, October 1 across the U.S. and internationally.

The law requires that all publicly held domestic or foreign companies headquartered in California have at least one female director on their boards by the end of 2019. The law imposes additional requirements for female board members after 2019. By the end of 2021, firms with five board members must have at least two female directors, while firms with six or more directors are required to have at least three female directors. For firms with four or fewer directors, a minimum of one female director is required. The law imposes penalties for non-compliance.[6] As of September 2018, Illinois, Massachusetts, Pennsylvania,

[5]"Gender diversity brings a variety of perspectives to the table that can help foster new and innovative ideas. It's not only the right thing to do, but it's also good for a company's bottom line."

[6]Each year, firms are subject to a compliance assessment and a monetary fine of $100,000 for the first violation. Subsequent violations are subject to a $300,000 penalty. The law also calls for the reporting of firms' compliance with the requirements through various reports and on the website of the California Secretary of State.
This is not the first effort by California legislators to address gender imbalances on corporate boards. In September 2013, California passed non-binding Senate Resolution 62 urging public companies in California to increase the number of women on their boards by one to three directors, depending upon their board size, by the end of 2016. However, only 20% of the companies headquartered in California met the goals outlined in the resolution (Board Governance Research LLC Report, 2017). California's adoption of this non-binding resolution led other states to follow.

and Colorado have passed similar non-binding resolutions urging more women directors on corporate boards for firms in these states. In addition, California led the U.S. in passing the first gender pay equity law. Also sponsored by Senator Jackson, in 2015, California passed Senate Bill 358, the California Fair Pay Act, a law that set a precedent for similar legislation in other states, most notably in Washington which passed gender pay equality legislation in 2018. Hwang et al. (2018) present a chronology of California Senate Bill 826 and related legislation. The required female board representation under California law is generally similar to or more stringent than under Norwegian law for small firms but is less stringent for large firms.

There is substantial debate over the legality of California's law. The California Chamber of Commerce, among others, has argued that the quotas mandated by the law are unconstitutional and represent a violation of the Federal Constitution and California's civil rights statutes.[7] Grundfest (2018) argues that since the law applies to firms headquartered in California, it creates a conflict with other state incorporation laws which do not mandate board gender diversity. Specifically, he argues that California law conflicts with Delaware law which allows the board to exercise its business judgment with respect to the number of women directors. To the extent there is an expectation that the law may eventually be overturned, the wealth effects we estimate will understate its economic consequences for shareholders.

Progress toward gender diversity in the boardroom is tangible. In the first fiscal quarter of 2018, nearly one-third of Russell 3000 new directorships went to women. Also, for the first time, fewer than 20 percent of companies in that index had all-male boards. Enterprise-wide initiatives have been undertaken by institutional investors, and corporate governance activists, alike. More importantly, the effectiveness of efforts by the private sector to tackle the intense resistance to quotas has rendered government intervention unnecessary as well as undesirable.

Proponents of gender diversity are pleased by the recent developments in the United States, as the market has driven the increase in the business community's enthusiasm for

[7]See California Chamber of Commerce, SB826 (Jackson): Board of Directors Oppose/Non-concurrence letter, August 30, 2018.

diverse boards. The California bill has legislated context-free quotas which may destabilize boards, undermine the sincere business case for increased gender diversity, and the larger societal goals of gender parity and board diversity would suffer as well.

7 Causality of the election of female CEO

We use the California Law as an exogenous shock to the diversity narrative in 2017 to claim causality in our analysis. From our previous results, we know that our diversity narrative channel is independent of the board gender diversity channel vis-a-vis the election of female CEOs. Hence, although this California Law has been repealed in 2022 and probably can no longer be used as an exogenous shock for board gender diversity mandate, it can still be used as an exogenous shock to the diversity narrative. We use the differences in the different specifications for our purposes. Our treatment group for a year consists of firms that do not have a female CEO until that year. Our control group comprises those firms which already have female CEOs.

We define the did variable as the interaction of the treatment group with the time of treatment. In Table 9, in Model 1, we find that the coefficient of did is significant at the 90% significance level. When we add control variables from our previous specifications, we notice that the coefficient of did is significant at a 95% confidence level in Model 2. The result is robust even after controlling for board gender diversity in Model 3. We further conduct robustness tests in Models 4 and 5 by adding the dummy for tech firms in Models 2 and 3, respectively and observe that the coefficient of did is still significant at the 95% level of significance.

With these strong results in our differences in differences approch, we can confidently claim that the diversity narrative from NYT causally elects female CEOs. Also, this channel is independent of the channel of changing the board gender diversity. It is this increased representation of gender diversity in firm leadership which can slant the direction a firm will take over several years. In fact, the election of female CEOs can further reinforce board gender diversity going forward (see Shivdasani and Yermack (1999) for a detailed account of this).

8 Ethnic Diversity in Leadership

In Table 10, we find that board gender diversity and diversity narrative do not have a first-order effect on the election of non-white CEOs. This is the first indication that firms do not need to cater to diversity narrative from NYT news or any board gender diversity mandate to introduce racial and/or ethnic diversity in firm leadership. Hence, diversity narrative is unable to provide equity in firm leadership in terms of ethnic diversity. The mix of nationalities on boards has a significant impact on the election of non-white CEOs. We also observe that CEOs with CFA and/or CPA certifications are less likely to be non-white. Non-white CEOs require significantly more qualifications like a Ph.D. or similar degree to get noticed and elected as CEOS. Also, tech firms overall have higher propensities of the election of non-white CEOs.

In Table 11, we notice that board gender diversity has a negative impact on the election of Asian CEOs. This is because Asia is a patriarchal society and board gender diversity does not go well with asian leadership. Also, the diversity narrative does not have any impact on the election of Asian CEOs. Obviously, the higher the mix of nationalities, the higher the chances of electing Asian CEOs. Non-technical education has a similar impact on the election of Asian CEOs. Namely Asian CEOs need Ph.D. or similar degrees to get noticed and elected as top executives.

Similar to asian CEOs, both board gender diversity and diversity narrative have an insignificant but negative impact on the election of Indian CEOs in Table 12. This implies that neither diversity narrative from NYT news nor board gender diversity has anything to do with the election of Indian CEOs. Obviously, boards with diverse nationalities are more likely to elect Indian CEOs. Education and tech industries have a similar impact. A non-technical certification like the CPA definitely does not get an Indian elected as the CEO of a firm. Also, tech industries definitely have higher propensity to elect Indian CEOs.

When Indians and Chinese are considered together in terms of being elected as CEOs, the mix of nationalities on boards has a comparatively lesser impact in Table 13. Even a coveted CFA certification does not get an asian elected as the CEO, if the pool of candidates consist of Indians and Chinese. If anything, CFA and CPA are definite deterrents of any possibilities of election if Indian and Chinese CEOs. Only hard technical education like a PhD or similar increase the chances of getting an Indian or Chinese elected at the highest levels of firm leadership.

But when Chinese CEOs are considered separately in Table 14, nationality mix in boards does not lead to their election. Education has similar effects on the election of Chinese CEOs per se. However, tech firms are less likely to elect Chinese CEOs. This implies Chinese CEOs are chosen in very specific cases because of idiosyncratic reasons. This is mostly when the firms have Chinese origins. This could also be to gain access to the Chinese market and sell the products or services to the Chinese consumers.

9 Discussion

Our results are indicative of the non-trivial relationship between diversity and equity. We find that gender diversity in firm leadership is relatively easy to achieve. We show that the diversity narrative from NYT is a key channel that can elect a female CEO in a firm other than tilting the composition of the board in terms of gender diversity. Because of this, the path to equity in terms of total compensation is relatively straightforward. Ethnic diversity in terms of firm leadership is significantly more difficult to achieve.

There is evidence that several high-ranking designations have been awarded to African Americans to encourage racial equity. This is not to be confused with ethnic diversity at the highest role in a public firm. The CEO of a firm is the public face and is subject to serious scrutiny. Moreover, African Americans are part of the fabric of American society. Electing a non-white non-American CEO for a firm requires serious justification. A narrative of diversity is hence not enough to bring about this change. Historically, Asians have had basic training in hard sciences, or in other words, have graduated with STEM (Science, Technology, Engineering, and Mathematics) degrees. Hence, all else equal, Asian leaders can offer the technical know-how that American CEOs cannot. Rising up the ranks of the corporate ladder and reaching the top position in a firm is significantly challenging for an Asian professional. This can only be achieved mainly in tech firms and other firms which promote a culture of excellence and hand leadership.

Among Asians, Indians, Chinese, and Japanese are the main contenders as we see in the data. Japanese professionals are native Japanese speakers and lack the ability to communicate coherently in fluent English. Both Indians and Chinese need to show hard evidence of a Ph.D. degree or having finished an MBA from a top business school. Since India has historically been a British colony, Indian professionals have grown up naturally with English as their first or second language. In India, English is not a means of communication but a social skill necessary to rise up the corporate ladder. Hence, Indians can sometimes become CEOs with MBA degrees and CFA certifications; whereas Chinese need to have Ph.D. degrees to be considered for the CEO position.

Arguably, there could be several other personal attributes of these Asian CEOs which make them leadership material. We intend to extend our analysis, in the future, by collecting more personal attributes of CEOs beyond education, ethnicity, age, etc. Cognitive abilities, financial literacy, ability to deal with high-pressure situations with calm and composure, and ability to listen to everyone's viewpoint and remain respectful towards everyone may all be determinants for the election of these non-white CEOs.

10 Conclusion

We provide evidence of the causal impact of the increase in diversity narrative on the election of female CEO. Female executives are not elected because they are better monitors than their male counterparts, i.e., the governance score does not affect the propensity of the election of female CEO. The election of female executives also does not corroborate the systematic improvement in work conditions or charitable donations. The search for an intangible non-financial value of firms from these gradual but persistent changes over time can have several implications. It may be difficult to distinguish firms, based on financial performance alone. More importantly, whether a push towards gender diversity and inclusion of minorities in the decision-making process at firms improves the well-being of society overall, remains to be seen. Definitely, these policies are unidirectional, since diversity narrative and board gender diversity increase the chances of female CEO election and cannot be reversed.

We show that education per se is not the sole determinant for the election of female CEO.

In fact, it it quite the opposite. If the firm requires CFA certification or other stringent criteria for CEO election, then the propensity of choosing a female CEO reduces drastically. However, the diversity narrative nudges the firms to cater to NYT news by electing firm leadership with gender diversity. The slant from news is translated into a higher representation of female executives.

We also find that this diversity narrative is unable to provide equity in terms of ethnic diversity in firm leadership. Ethnic diversity in firm leadership is much more challenging to achieve. Typically, tech firms who require a strong understanding of the product or the process control require CEOs with at least a CFA or preferably a PhD degree. Hence, they choose non-white CEOs, namely asian CEOs. Evn among the Asians, the Indians turn out to the be biggest contenders since Indians have been raised in a English-speaking environment and arguably have had to overcome several hurdles to even make it to these top tech firms. This enables Indians to climb up the corporate ladder relatively faster and showcase their leadership skills in a fiercely paced fast moving technological landscape with ever changing growth opportunities. It requires an exceptionally steady set of hands to lead a technology firm to differentiate itself and also to maintain their position in this highly competitive market. Also, having been raised in a democratic country, Indians appreciate the idea of unity in diversity and are very good listeners and people managers.

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Figure 1: Estimation Scheme

This figure plots the rolling estimation scheme to construct the diversity score. Every month t, news articles in the previous 120 months (including month t) are used to compute word vectors via *word2vec*. These word vectors are used to construct a dynamic 100-word diversity dictionary. Articles in month $t+1$ are then used to construct the real-time diversity score.

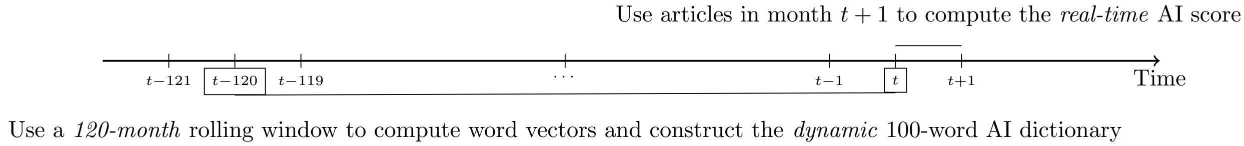
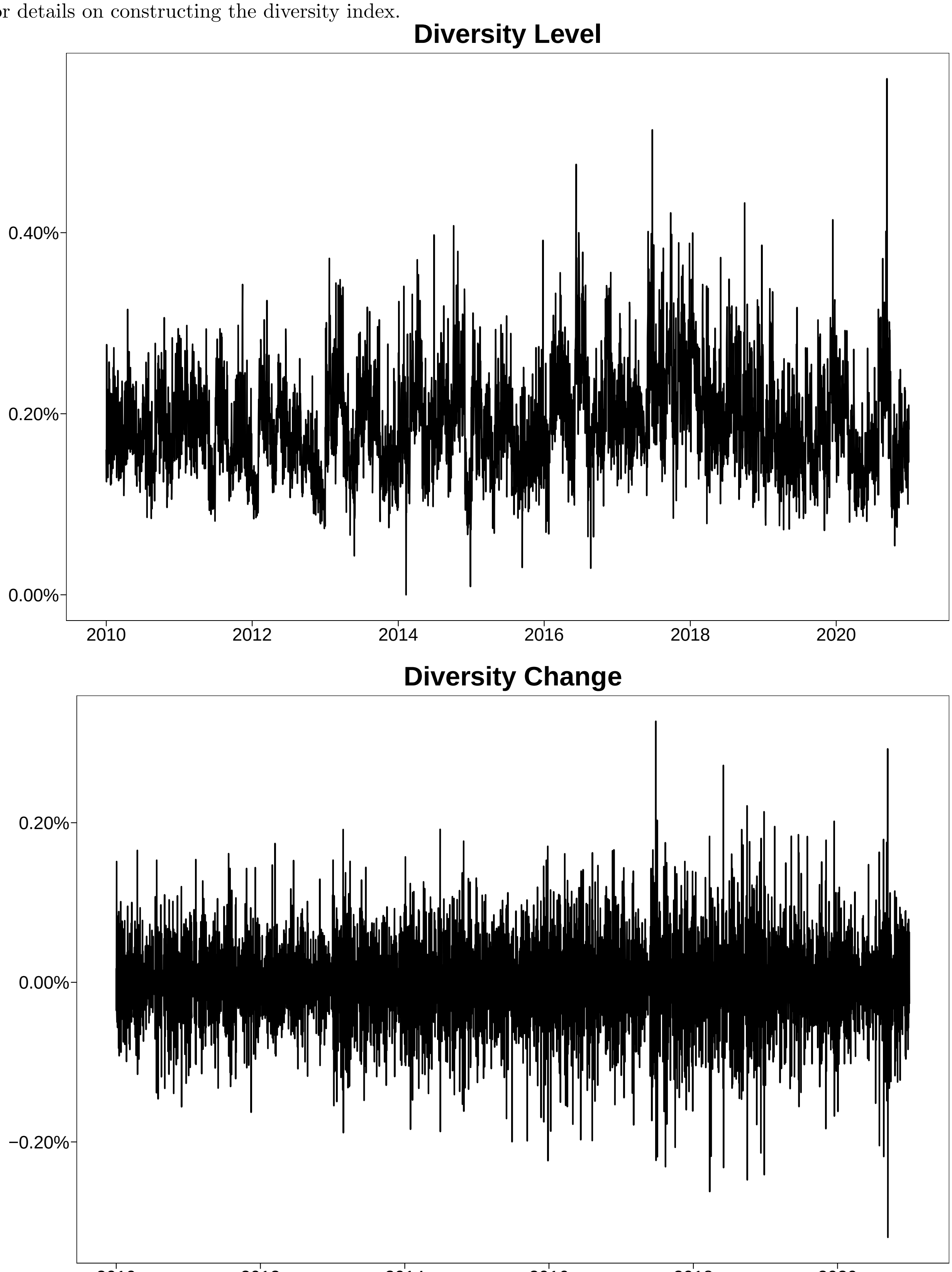


Figure 2: Diversity Word Cloud

This figure plots the word cloud for terms related to *diversity* in the New York Times articles from 2010 to 2020. The bigger the size, the more frequently the term appears in news articles. See section 2 for details on extracting these terms.

Figure 3: Time Series of Diversity Score

This figure plots the time series of the daily diversity index in Panel A and the change in daily diversity index (Panel B) constructed from the New York Times articles. The sample is from 2010 to 2020. See section 2 for details on constructing the diversity index.



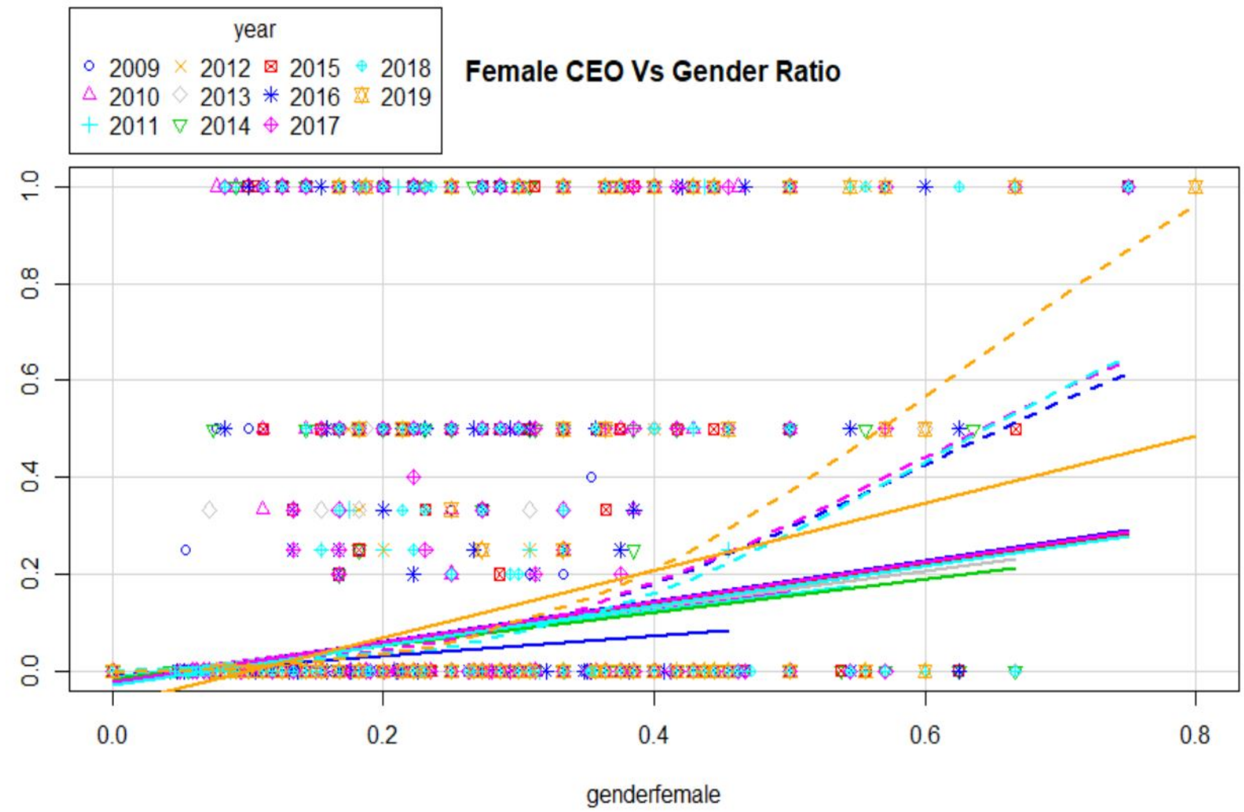


Figure 4: Board Gender Diversity and Female CEO: We explore the impact of this novel diversity narrative from NYT alongside board gender diversity which has been relatively well-studied. In Figure 4, it is evident that the relationship between the election of female CEO the board gender diversity becomes exponential from 2016 onwards. The yearly curves become steeper, and this exponential change occurs when the threshold of 40% for board gender diversity is breached. Essentially, a critical mass of gender diversity at the board level leads to an almost sure election of female CEO in the firm.

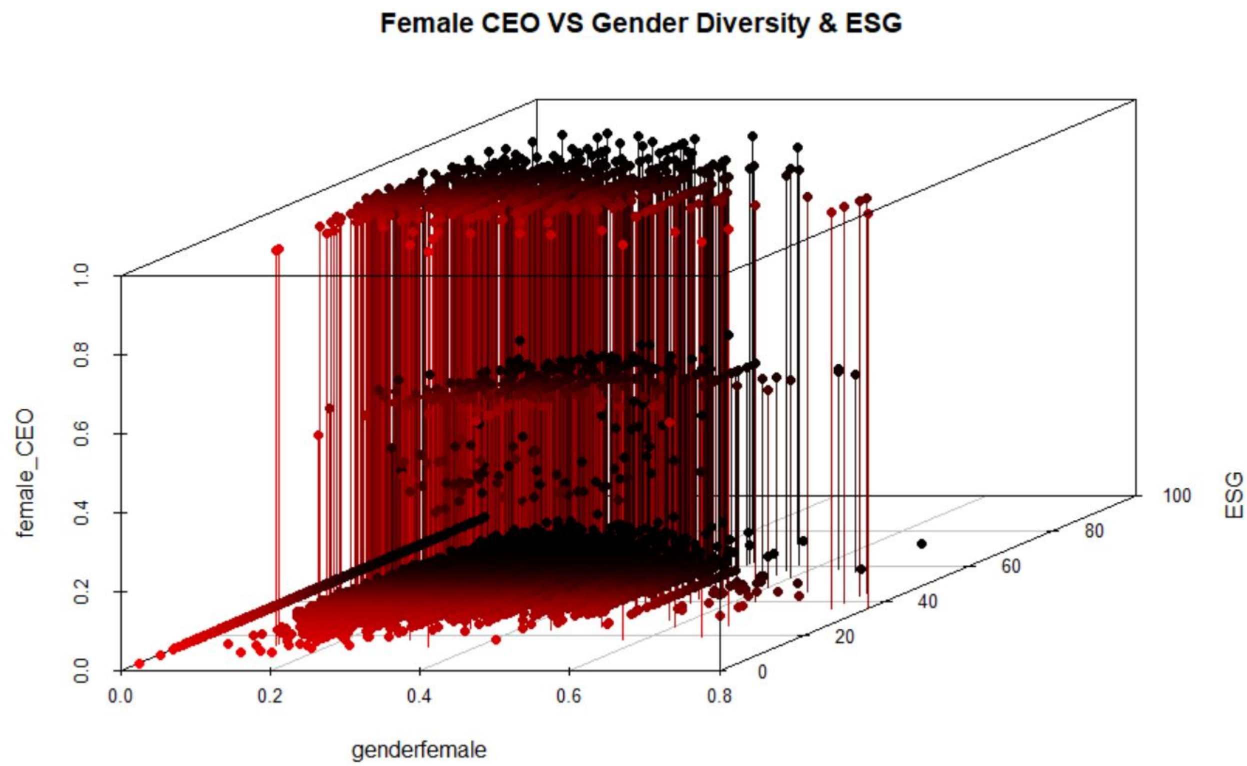


Figure 5: Female CEO Vs Board Gender Diversity and ESG: We also visualize the evidence of this critical mass in a 3-dimensional diagram where the propensity of the election of female CEO is plotted against the board gender diversity and the ESG scores.

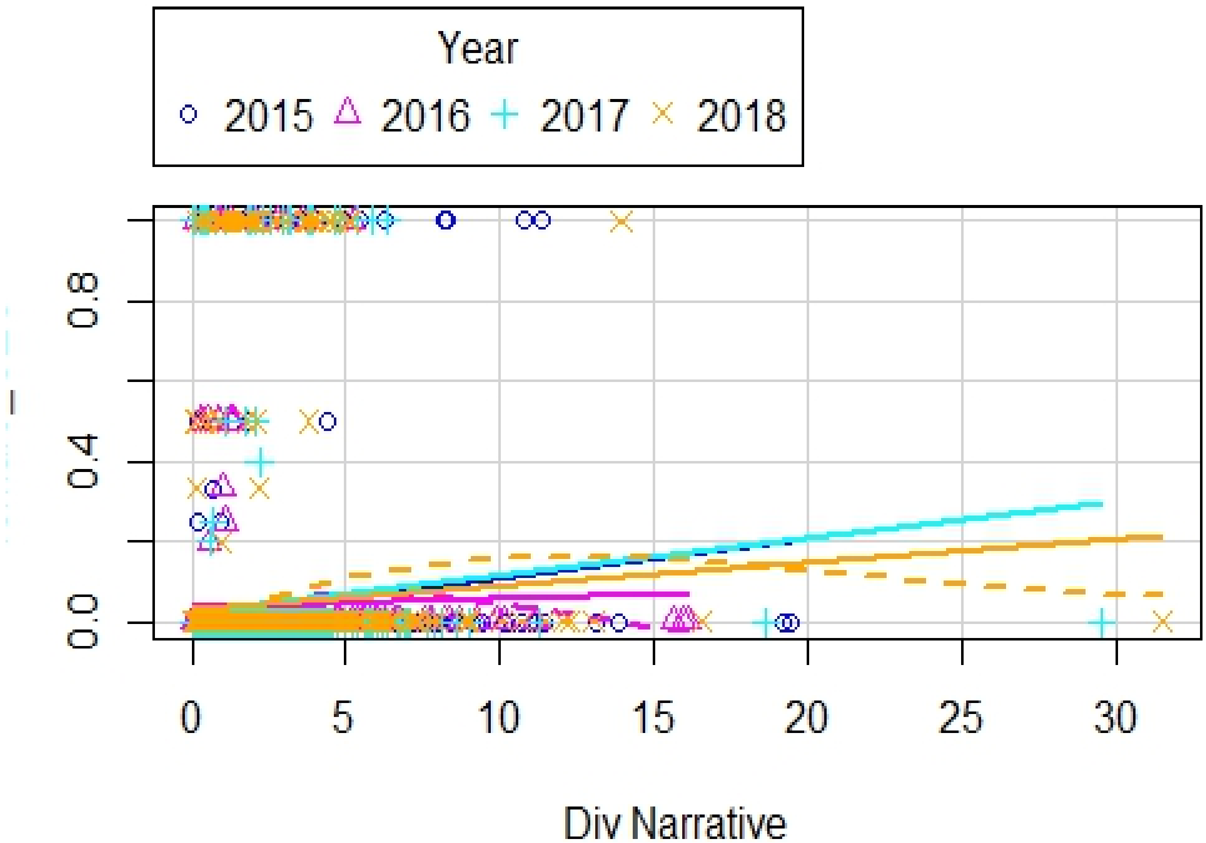


Figure 6: Diversity Narrative and Female CEO for Positive Beta: We find similar evidence of an increase in the probability of the election of female CEO with increasing beta of diversity narrative. The effect is pronounced for 2017, which we later use for causal analysis. Interestingly, in Fig 6 and Fig 7, we see this relationship of female CEO with NYT diversity narrative whenever the absolute value of beta increases.

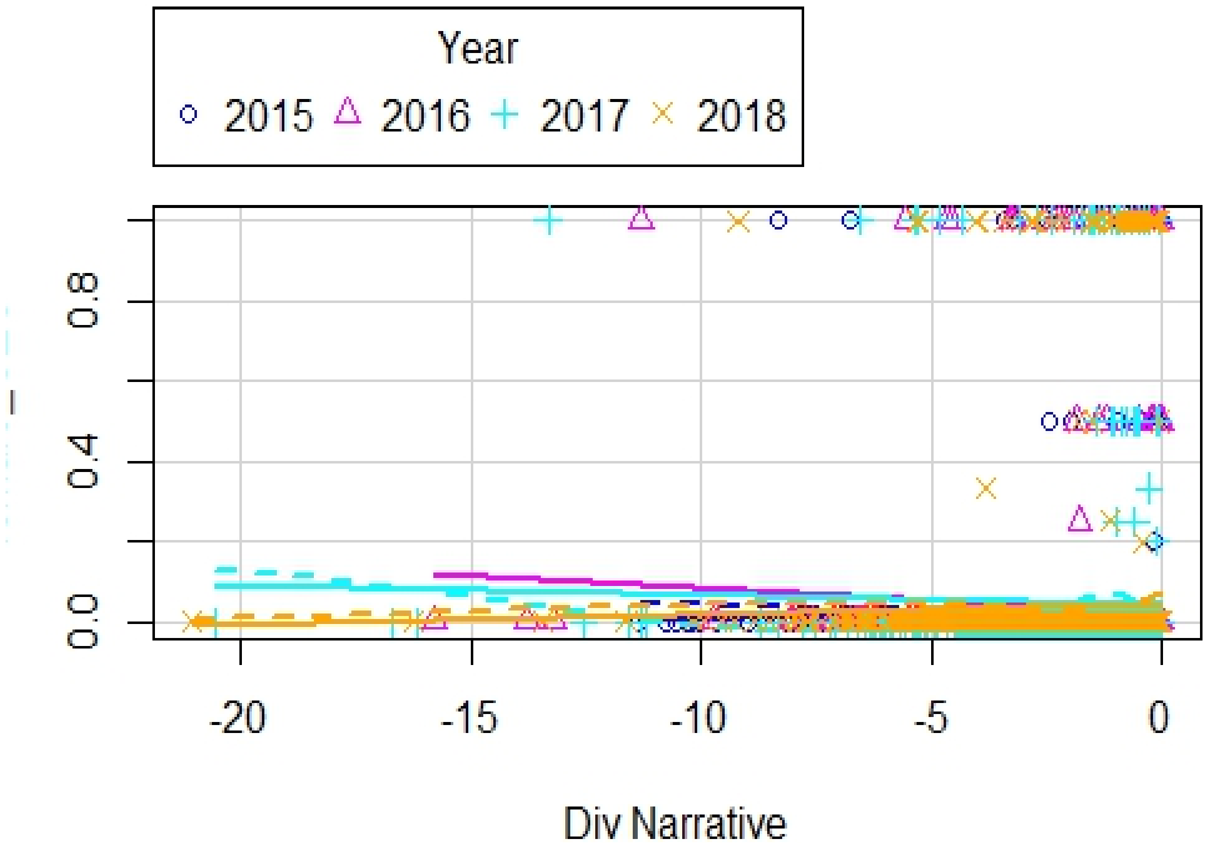


Figure 7: Diversity Narrative and Female CEO for Negative Beta: We find similar evidence of an increase in the probability of the election of female CEO with increasing beta of diversity narrative. The effect is pronounced for 2017, which we later use for causal analysis. Interestingly, in Fig 6 and Fig 7, we see this relationship of female CEO with NYT diversity narrative whenever the absolute value of beta increases.

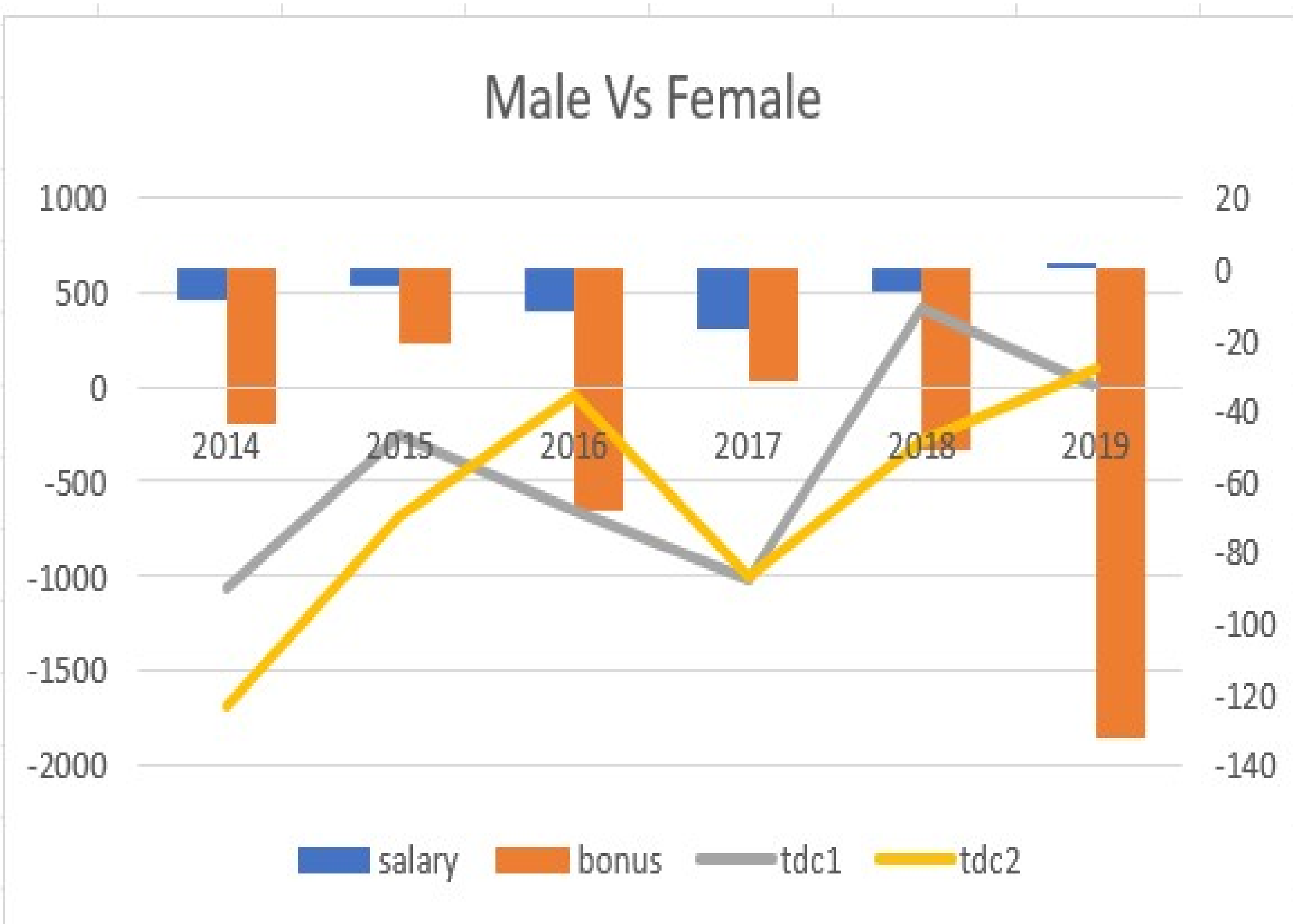


Figure 8: Male Vs Female Equity in Compensation: The first evidence of equity from this diversity narrative shows up in the compensation gaps between male and female CEOs over time. Figure 8 plots the differences in various compensation measures between male and female CEOs. From TDC1 and TDC2 plotted in the primary axis, we observe that the total compensation of male and female counterparts become more equitable from 2014-2019. In fact, the diversity narrative may have led to the election of female CEOs and slanted the female leadership ratio in firms. But because of search friction in finding equally capable and qualified female CEOS, the female CEOs may have had higher total compensation. However, over time, this slant has created equitable total compensation. Looking at the base salary and bonus in the secondary axis, we observe that the base salary is becoming more equitable across male and female CEOs. However, the bonus component of the compensation increases significantly for female CEOs. This points to an exciting mechanism of attaining equity in total compensation.

N = 14463	Min	1st Q	Median	Mean	3rd Q	Max	NA's
female_CEO	0.00	0.00	0.00	0.034	0.00	1.00	
b_d_diversity	-21.069	-1.175	0.005	0.009	1.155	76.113	3
genderdiv	0.00	0.077	0.133	0.144	0.222	0.750	
tech	0.00	0.00	0.00	0.068	0.00	1.00	
nationalitymix	0.00	0.00	0.00	0.084	0.10	0.90	779
numberdirectors	3.00	8.00	9.00	9.442	11.00	33.00	
networksize	8.0	292.5	846.0	1382.8	1910.0	18666.0	300
E	0.00	37.67	45.33	46.60	55.00	100.00	1130
S	0.00	43.58	49.50	49.77	55.67	89.00	13
G	0.00	39.67	47.33	47.17	55.00	91.00	87
EMP	0.00	42.33	49.67	49.41	56.33	92.00	33
CIT	0.00	43.67	49.00	50.13	56.33	100.00	149
bindep	0.273	0.667	0.833	0.7765	0.889	0.952	
age	29.00	57.00	61.00	61.44	66.00	95.00	61
CFA_CEO	0.00	0.00	0.00	0.008	0.00	1.00	
CPA_CEO	0.00	0.00	0.00	0.068	0.00	1.00	
PhD_CEO	0.00	0.00	0.00	0.023	0.00	1.00	

Table 1: Summary of Data for election of female CEO: We provide the summary statistics of the merged data from BoardEx, ExecuComp, and diversity exposures (i.e. betas). As is evident from the third quartile being zero, the number of female CEOs is clearly unbalanced compared to the historic and even current number of male CEOs. The diversity narrative score from NYT (b_d_diversity) is fairly symmetric. The board gender diversity (genderdiv) is variable between 0 and 1. We see around 6.8% firm-year observations from the tech industry. We also provide summaries of the mix of nationalities across board members, the number of executive and independent directors, the network size of the directors, and environment, social, governance, employment, and charity scores from OWL Analytics. As expected, we observe a right-skewed distribution for board independence. The age of CEOs is around 61.5 on average and is symmetric. There are 0.8% CEOs who hold the coveted CFA certification, possibly from Ivy League business schools. CPA is an easier more general public accounting certification for a CEO who generally rises up the ranks from an accounting background. There are around 2.3% of CEOs are PhDs, mostly in tech companies where technical expertise is a necessary criterion for being in firm leadership.

N = 14435	Min	1st Q	Median	Mean	3rd Q	Max	NA's
female_CEO	0.00	0.00	0.00	0.034	0.00	1.00	
b_d_diversity	-21.069	-1.177	0.004	0.007	1.154	76.113	3
genderdiv	0.00	0.077	0.133	0.144	0.22	0.75	
tech	0.00	0.00	0.00	0.068	0.00	1.00	
nationalitymix	0.00	0.00	0.00	0.083	0.10	0.90	779
numberdirectors	3.00	8.00	9.00	9.44	11.00	33.00	
bindep	0.273	0.667	0.833	0.776	0.889	0.952	
age	29.00	57.00	61.00	61.44	66.00	95.00	58
CFA_CEO	0.00	0.00	0.00	0.008	0.00	1.00	
CPA_CEO	0.00	0.00	0.00	0.068	0.00	1.00	
PhD_CEO	0.00	0.00	0.00	0.023	0.00	1.00	
asian	0.00	0.00	0.00	0.031	0.00	1.00	
non_white	0.00	0.00	0.00	0.061	0.00	1.00	
Indian	0.00	0.00	0.00	0.011	0.00	1.00	
Chinese	0.00	0.00	0.00	0.008	0.00	1.00	

Table 2: Summary of Final Data for CEO election based on Ethnicity: We summarize the merger with CEO ethnicity from ExecuComp. Clearly, the CEOs with coveted certifications of CFA, CPA, or the highest educational degree of a Ph.D. are non-white.

N = 7220	Min	1st Q	Median	Mean	3rd Q	Max	NA's
female_CEO	0.00	0.00	0.00	0.035	0	1.00	3
b_d_diversity	-21.069	-2.272	-1.177	0.007	2.224	76.113	3
genderdiv	0.00	0.00	0.125	0.132	0.20	0.75	3
tech	0.00	0.00	0.00	0.075	0.00	1.00	3
nationalitymix	0.00	0.00	0.00	0.083	0.00	0.80	426
numberdirectors	3.00	7.00	9.00	8.979	10.00	32.00	3
bindep	0.273	0.667	0.833	0.778	0.889	0.944	3
age	29.00	57.00	61.00	61.43	66.00	95.00	37
CFA_CEO	0.00	0.00	0.00	0.007	0.00	1.00	3
CPA_CEO	0.00	0.00	0.00	0.062	0.00	1.00	3
PhD_CEO	0.00	0.00	0.00	0.029	0.00	1.00	3
asian	0.00	0.00	0.00	0.031	0.00	1.00	3
non_white	0.00	0.00	0.00	0.061	0.00	1.00	3
Indian	0.00	0.00	0.00	0.011	0.00	1.00	3
Chinese	0.00	0.00	0.00	0.008	0.00	1.00	3

Table 3: Summary of Final Data for CEO election based on Ethnicity beyond Q1, Q3 of diversity narrative: we test for the kurtosis of the data. We find that if we only take the data beyond the first and third quartiles of the diversity narrative scores, we see the same percentage of CEOs with CFA, CPA, or Ph.D. This further corroborates our premise that firms that are prone to cater to the NYT diversity narrative happen to elect CEOs with hard evidence of education or certifications, which arguably is present mostly in non-white leaders.

year	salary	bonus	tdc1	tdc2
2013	691.2802	184.5967	4777.721	6872.262
2014	711.4688	192.4286	5069.368	6105.951
2015	722.3178	185.2085	5256.248	6700.38
2016	745.9275	161.4821	5616.029	6954.685
2017	775.9316	181.976	6176.653	7857.352
2018	804.423	161.2324	6645.183	8036.056
2019	825.4279	173.7935	6797.107	8175.374

Table 4: Average Compensation of Male CEOs: In Tables 4 and 5, we document the average compensation measures of male and female CEOs across time, respectively. Overall, the trend is increasing however, the relative changes point us to a very interesting way of attaining equity in total compensation.

year	salary	bonus	tdc1	tdc2
2013	688.3099	228.2397	5211.014	5658.758
2014	720.0182	236.0373	6139.564	7800.498
2015	727.2151	206.1178	5515.336	7386.321
2016	757.9385	229.5604	6266.731	6992.602
2017	793.2844	213.9801	7192.946	8856.365
2018	810.9151	212.1808	6229.652	8322.602
2019	823.6858	306.3007	6790.118	8086.164

Table 5: Average Compensation of Female CEOs: In Tables 4 and 5, we document the average compensation measures of male and female CEOs across time, respectively. Overall, the trend is increasing however, the relative changes point us to a very interesting way of attaining equity in total compensation.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	0.0016^{*}		0.0018^{**}	0.0016^{*}		0.0018^{**}
	(0.0006)		(0.0006)	(0.0006)		(0.0006)
genderdiv	0.4183^{***}	0.4184^{***}		0.4171^{***}	0.4172^{***}	
	(0.0638)	(0.0639)		(0.0636)	(0.0638)	
nationalitymix	-0.0348^{*}	-0.0344^{*}	-0.0304	-0.0334^{*}	-0.0330^{*}	-0.0287
	(0.0169)	(0.0168)	(0.0161)	(0.0164)	(0.0163)	(0.0156)
bindep	0.1034^{***}	0.1027^{***}	0.0859^{**}	0.1031^{***}	0.1025^{***}	0.0856^{**}
	(0.0269)	(0.0269)	(0.0253)	(0.0269)	(0.0270)	(0.0253)
ceodual	0.0134	0.0134	0.0107	0.0132	0.0132	0.0104
	(0.0088)	(0.0088)	(0.0086)	(0.0088)	(0.0088)	(0.0087)
age	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
tech				-0.0172	-0.0174	-0.0218
				(0.0120)	(0.0120)	(0.0109)
Num. obs.	12355	12358	12355	12355	12358	12355
factor(state)	56	56	56	56	56	56
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.1228	0.1222	0.0677	0.1234	0.1228	0.0686
R^2 (proj model)	0.0684	0.0678	0.0099	0.0690	0.0684	0.0108
Adj. R^2 (full model)	0.1173	0.1167	0.0618	0.1177	0.1173	0.0627
Adj. R^2 (proj model)	0.0675	0.0669	0.0089	0.0680	0.0675	0.0098

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 6: Fixed Effect Models: We control for the number of directors, network size, E & G scores, whether the CEO has a dual role, age. Model 1 estimates the impact of both board gender diversity and the diversity narrative from *NYT* o on the election of female CEOs in the exact specification. As is evident, both these channels are statistically significant. Other than that, the nationality mix on the board negatively affects the election of female CEOs. This is because people of different nationalities perceive female leadership differently. Also, board independence leads to the election of female CEOs.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	0.0016^{*}		0.0018^{**}	0.0016^{*}		0.0018^{**}
	(0.0007)		(0.0007)	(0.0006)		(0.0007)
genderdiv	0.4204^{***}	0.4205^{***}		0.4192^{***}	0.4193^{***}	
	(0.0638)	(0.0639)		(0.0636)	(0.0637)	
nationalitymix	-0.0374^{*}	-0.0371^{*}	-0.0324	-0.0360^{*}	-0.0357^{*}	-0.0307
	(0.0180)	(0.0179)	(0.0171)	(0.0175)	(0.0174)	(0.0165)
numberdirectors	-0.0020	-0.0020	0.0013	-0.0022	-0.0022	0.0010
	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)	(0.0015)
networksize	-0.00	-0.00	0.00	-0.0000	-0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
bindep	0.1015^{***}	0.1008^{***}	0.0845^{***}	0.1013^{***}	0.1006^{***}	0.0844^{***}
	(0.0256)	(0.0257)	(0.0242)	(0.0257)	(0.0257)	(0.0242)
E	0.0002	0.0002	0.0004	0.0002	0.0002	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
S	0.2428	0.2540	0.1651	0.2509	0.2618	0.1758
	(0.4322)	(0.4349)	(0.4017)	(0.4296)	(0.4321)	(0.3993)
G	-0.0001	-0.0001	0.0004	-0.0001	-0.0001	0.0004
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
EMP	-0.1214	-0.1270	-0.0821	-0.1254	-0.1309	-0.0874
	(0.2161)	(0.2175)	(0.2008)	(0.2148)	(0.2161)	(0.1996)
CIT	-0.1215	-0.1271	-0.0830	-0.1255	-0.1309	-0.0883
	(0.2162)	(0.2176)	(0.2010)	(0.2149)	(0.2162)	(0.1998)
ceodual	0.0138	0.0138	0.0110	0.0136	0.0136	0.0107
	(0.0089)	(0.0089)	(0.0087)	(0.0089)	(0.0089)	(0.0088)
age	-0.0004	-0.0004	-0.0005	-0.0005	-0.0005	-0.0006
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CFA_CEO	-0.0363^{**}	-0.0362^{**}	-0.0225^{**}	-0.0360^{*}	-0.0359^{*}	-0.0222^{**}
	(0.0133)	(0.0131)	(0.0070)	(0.0137)	(0.0135)	(0.0069)
CPA_CEO	-0.0030	-0.0029	-0.0035	-0.0036	-0.0035	-0.0043
	(0.0243)	(0.0243)	(0.0246)	(0.0246)	(0.0246)	(0.0249)
PhD_CEO	0.0320	0.0324	0.0240	0.0315	0.0319	0.0234
	(0.0392)	(0.0391)	(0.0403)	(0.0394)	(0.0393)	(0.0406)
tech				-0.0169	-0.0171	-0.0217
				(0.0124)	(0.0124)	(0.0113)
Num. obs.	12355	12358	12355	12355	12358	12355
factor(state)	56	56	56	56	56	56
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.1238	0.1233	0.0682	0.1244	0.1238	0.0691
R^2 (proj model)	0.0695	0.0689	0.0104	0.0701	0.0695	0.0114
Adj. R^2 (full model)	0.1180	0.1175	0.0621	0.1185	0.1180	0.0630
Adj. R^2 (proj model)	0.0683	0.0678	0.0092	0.0688	0.0683	0.0101

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 7: Fixed Effect Models with Education

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	0.0014*		0.0016*	0.0014		0.0016*
	(0.0007)		(0.0007)	(0.0007)		(0.0007)
genderdiv	0.4119***	0.4119***		0.4116***	0.4116***	
	(0.0607)	(0.0608)		(0.0606)	(0.0607)	
size	−0.0046	−0.0046	0.0008	−0.0047	−0.0047	0.0006
	(0.0032)	(0.0032)	(0.0030)	(0.0033)	(0.0033)	(0.0031)
nationalitymix	−0.0225	−0.0222	−0.0180	−0.0216	−0.0213	−0.0169
	(0.0228)	(0.0228)	(0.0212)	(0.0221)	(0.0220)	(0.0205)
numberdirectors	−0.0002	−0.0002	0.0005	−0.0003	−0.0003	0.0005
	(0.0021)	(0.0021)	(0.0022)	(0.0021)	(0.0021)	(0.0022)
networksize	−0.0000	−0.0000	0.0000	−0.0000	−0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
bindep	0.0774*	0.0768*	0.0819*	0.0770*	0.0765*	0.0815*
	(0.0339)	(0.0340)	(0.0331)	(0.0341)	(0.0342)	(0.0332)
E	0.0004	0.0004	0.0005	0.0004	0.0004	0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
S	0.4598	0.4729	0.4142	0.4639	0.4768	0.4193
	(0.4908)	(0.4926)	(0.4749)	(0.4897)	(0.4913)	(0.4742)
G	−0.0001	−0.0001	0.0004	−0.0001	−0.0001	0.0004
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0004)
EMP	−0.2298	−0.2363	−0.2066	−0.2318	−0.2382	−0.2091
	(0.2455)	(0.2464)	(0.2375)	(0.2449)	(0.2457)	(0.2371)
CIT	−0.2302	−0.2367	−0.2077	−0.2322	−0.2387	−0.2103
	(0.2455)	(0.2464)	(0.2376)	(0.2450)	(0.2458)	(0.2372)
ceodual	0.0110	0.0110	0.0096	0.0109	0.0109	0.0094
	(0.0106)	(0.0106)	(0.0107)	(0.0106)	(0.0106)	(0.0107)
age	−0.0003	−0.0003	−0.0004	−0.0003	−0.0003	−0.0004
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
CFA_CEO	−0.0360**	−0.0358**	−0.0208*	−0.0360**	−0.0359**	−0.0208*
	(0.0126)	(0.0125)	(0.0086)	(0.0128)	(0.0127)	(0.0086)
CPA_CEO	−0.0069	−0.0068	−0.0091	−0.0071	−0.0070	−0.0094
	(0.0237)	(0.0237)	(0.0241)	(0.0240)	(0.0241)	(0.0244)
PhD_CEO	0.0298	0.0301	0.0245	0.0295	0.0298	0.0242
	(0.0380)	(0.0379)	(0.0391)	(0.0382)	(0.0381)	(0.0393)
tech				−0.0097	−0.0098	−0.0122
				(0.0196)	(0.0196)	(0.0181)
Num. obs.	15904	15907	15904	15904	15907	15904
factor(state)	56	56	56	56	56	56
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.1225	0.1221	0.0715	0.1227	0.1223	0.0717
R^2 (proj model)	0.0639	0.0635	0.0094	0.0641	0.0636	0.0097
Adj. R^2 (full model)	0.1180	0.1176	0.0667	0.1181	0.1177	0.0669
Adj. R^2 (proj model)	0.0629	0.0625	0.0084	0.0630	0.0626	0.0086

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 8: Fixed Effect Models with Education and Size

	Model 1	Model 2	Model 3	Model 4	Model 5
treat	0.7852***	0.7726***	0.7680***	0.7725***	0.7680***
	(0.0471)	(0.0487)	(0.0493)	(0.0487)	(0.0493)
did	0.0504	0.0607*	0.0592*	0.0607*	0.0592*
	(0.0274)	(0.0287)	(0.0285)	(0.0287)	(0.0285)
genderdiv			0.0483*		0.0483*
			(0.0190)		(0.0190)
tech				−0.0006	−0.0004
				(0.0037)	(0.0038)
size		−0.0030	−0.0036	−0.0030	−0.0036
		(0.0018)	(0.0019)	(0.0018)	(0.0019)
nationalitymix		−0.0000	−0.0007	0.0000	−0.0007
		(0.0061)	(0.0060)	(0.0061)	(0.0060)
numberdirectors		−0.0012	−0.0013	−0.0012	−0.0013
		(0.0010)	(0.0010)	(0.0010)	(0.0010)
networksize		−0.0000*	−0.0000*	−0.0000*	−0.0000*
		(0.0000)	(0.0000)	(0.0000)	(0.0000)
bindep		0.0474***	0.0471***	0.0474***	0.0471***
		(0.0083)	(0.0081)	(0.0083)	(0.0081)
ceodual		0.0089***	0.0091***	0.0089***	0.0091***
		(0.0025)	(0.0024)	(0.0025)	(0.0024)
age		0.0000	0.0000	0.0000	0.0000
		(0.0002)	(0.0002)	(0.0002)	(0.0002)
CFA_CEO		0.0025	0.0006	0.0025	0.0006
		(0.0052)	(0.0056)	(0.0053)	(0.0057)
CPA_CEO		0.0029	0.0031	0.0029	0.0031
		(0.0052)	(0.0053)	(0.0052)	(0.0053)
PhD_CEO		0.0037	0.0044	0.0037	0.0044
		(0.0070)	(0.0069)	(0.0070)	(0.0069)
Num. obs.	18960	15907	15907	15907	15907
factor(state)	56	56	56	56	56
factor(Year)	11	11	11	11	11
R^2 (full model)	0.8926	0.8929	0.8936	0.8929	0.8936
R^2 (proj model)	0.8858	0.8858	0.8865	0.8858	0.8865
Adj. R^2 (full model)	0.8922	0.8924	0.8930	0.8924	0.8930
Adj. R^2 (proj model)	0.8858	0.8856	0.8864	0.8856	0.8863

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 9: Causal Results for Female CEO Election: In Model 1, we find that the coefficient of did is significant at the 90% significance level. When we add control variables from our previous specifications, we notice that the coefficient of did is significant at a 95% confidence level in Model 2. The result is robust even after controlling for board gender diversity in Model 3. We further conduct robustness tests in Models 4 and 5 by adding the dummy for tech firms in Models 2 and 3, respectively and observe that the coefficient of did is still significant at the 95% level of significance.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	0.0002		0.0002	0.0002		0.0002
	(0.0009)		(0.0009)	(0.0009)		(0.0009)
genderdiv	0.0340	0.0340		0.0342	0.0342	
	(0.0301)	(0.0303)		(0.0308)	(0.0309)	
nationalitymix	0.1031***	0.1032***	0.1039***	0.1029***	0.1029***	0.1037***
	(0.0225)	(0.0225)	(0.0229)	(0.0223)	(0.0222)	(0.0226)
numberdirectors	0.0014	0.0014	0.0017*	0.0014	0.0014	0.0018*
	(0.0010)	(0.0010)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
bindep	−0.0168	−0.0170	−0.0188	−0.0168	−0.0169	−0.0188
	(0.0181)	(0.0179)	(0.0171)	(0.0181)	(0.0179)	(0.0171)
age	−0.0001	−0.0001	−0.0001	−0.0000	−0.0000	−0.0001
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
CFA_CEO	−0.0390*	−0.0390*	−0.0378*	−0.0391*	−0.0390*	−0.0378*
	(0.0177)	(0.0177)	(0.0180)	(0.0176)	(0.0176)	(0.0179)
CPA_CEO	−0.0019	−0.0018	−0.0021	−0.0017	−0.0017	−0.0020
	(0.0138)	(0.0138)	(0.0137)	(0.0138)	(0.0138)	(0.0137)
PhD_CEO	0.0588**	0.0589**	0.0583**	0.0589**	0.0590**	0.0584**
	(0.0190)	(0.0190)	(0.0193)	(0.0188)	(0.0188)	(0.0191)
tech				0.0029	0.0029	0.0025
				(0.0143)	(0.0143)	(0.0139)
Num. obs.	13599	13602	13599	13599	13602	13599
factor(state)	55	55	55	55	55	55
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.0310	0.0310	0.0308	0.0310	0.0310	0.0308
R^2 (proj model)	0.0075	0.0075	0.0073	0.0075	0.0075	0.0073
Adj. R^2 (full model)	0.0258	0.0258	0.0256	0.0257	0.0258	0.0256
Adj. R^2 (proj model)	0.0068	0.0069	0.0067	0.0068	0.0068	0.0066

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 10: We find that board gender diversity and diversity narrative do not have a first-order effect on the election of non-white CEOs. This is the first indication that firms do not need to cater to diversity narrative from NYT news or any board gender diversity mandate to introduce racial and/or ethnic diversity in firm leadership. Hence, diversity narrative is unable to provide equity in firm leadership in terms of ethnic diversity.
The mix of nationalities on boards has a significant impact on the election of non-white CEOs. We also observe that CEOs with CFA and/or CPA certifications are less likely to be non-white. Non-white CEOs require significantly more qualifications like a Ph.D. or similar degree to get noticed and elected as CEOS. Also, tech firms overall have higher propensities of the election of non-white CEOs.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	0.0000		−0.0000	0.0000		0.0000
	(0.0005)		(0.0005)	(0.0005)		(0.0005)
genderdiv	−0.0165	−0.0165		−0.0162	−0.0162	
	(0.0235)	(0.0236)		(0.0242)	(0.0244)	
nationalitymix	0.0453^{**}	0.0453^{**}	0.0449^{*}	0.0448^{**}	0.0448^{**}	0.0444^{**}
	(0.0168)	(0.0168)	(0.0170)	(0.0162)	(0.0162)	(0.0164)
numberdirectors	0.0001	0.0001	−0.0001	0.0002	0.0002	0.0000
	(0.0007)	(0.0007)	(0.0006)	(0.0007)	(0.0007)	(0.0006)
bindep	0.0172	0.0172	0.0182	0.0172	0.0172	0.0182
	(0.0102)	(0.0102)	(0.0098)	(0.0102)	(0.0101)	(0.0098)
age	−0.0001	−0.0001	−0.0001	−0.0001	−0.0000	−0.0000
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CFA_CEO	−0.0168	−0.0168	−0.0174	−0.0169	−0.0169	−0.0175
	(0.0129)	(0.0129)	(0.0131)	(0.0128)	(0.0128)	(0.0129)
CPA_CEO	−0.0012	−0.0012	−0.0011	−0.0010	−0.0010	−0.0009
	(0.0110)	(0.0110)	(0.0111)	(0.0110)	(0.0110)	(0.0110)
PhD_CEO	0.0553^{**}	0.0553^{**}	0.0555^{**}	0.0555^{**}	0.0555^{**}	0.0557^{**}
	(0.0194)	(0.0193)	(0.0196)	(0.0192)	(0.0191)	(0.0194)
tech				0.0053	0.0053	0.0054
				(0.0142)	(0.0142)	(0.0141)
Num. obs.	13599	13602	13599	13599	13602	13599
factor(state)	55	55	55	55	55	55
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.0383	0.0383	0.0382	0.0383	0.0383	0.0382
R^2 (proj model)	0.0045	0.0045	0.0044	0.0046	0.0046	0.0045
Adj. R^2 (full model)	0.0331	0.0331	0.0330	0.0330	0.0331	0.0330
Adj. R^2 (proj model)	0.0038	0.0039	0.0038	0.0038	0.0039	0.0038

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 11: We notice that board gender diversity has a negative impact on the election of Asian CEOs. This is because Asia is a patriarchal society and board gender diversity does not go well with asian leadership. Also, the diversity narrative does not have any impact on the election of Asian CEOs. Obviously, the higher the mix of nationalities, the higher the chances of electing Asian CEOs. Non-technical education has a similar impact on the election of Asian CEOs. Namely Asian CEOs need Ph.D. or similar degrees to get noticed and elected as top executives.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	-0.0001		-0.0001	-0.0001		-0.0001
	(0.0002)		(0.0002)	(0.0002)		(0.0002)
genderdiv	-0.0021	-0.0016		-0.0003	0.0002	
	(0.0165)	(0.0167)		(0.0158)	(0.0159)	
nationalitymix	0.0680^{**}	0.0677^{**}	0.0679^{**}	0.0648^{**}	0.0646^{**}	0.0648^{**}
	(0.0250)	(0.0250)	(0.0248)	(0.0235)	(0.0236)	(0.0235)
numberdirectors	-0.0015^{*}	-0.0015^{*}	-0.0015^{*}	-0.0011	-0.0011	-0.0011
	(0.0006)	(0.0006)	(0.0007)	(0.0005)	(0.0005)	(0.0006)
bindep	-0.0015	-0.0010	-0.0014	-0.0011	-0.0006	-0.0011
	(0.0176)	(0.0177)	(0.0175)	(0.0171)	(0.0172)	(0.0170)
age	-0.0003	-0.0003	-0.0003	-0.0001	-0.0001	-0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CFA_CEO	-0.0070	-0.0071	-0.0071	-0.0075^{*}	-0.0076^{*}	-0.0075^{*}
	(0.0039)	(0.0039)	(0.0037)	(0.0037)	(0.0037)	(0.0036)
CPA_CEO	-0.0088^{**}	-0.0090^{**}	-0.0088^{**}	-0.0076^{*}	-0.0077^{*}	-0.0076^{*}
	(0.0027)	(0.0026)	(0.0027)	(0.0030)	(0.0030)	(0.0030)
PhD_CEO	0.0089	0.0088	0.0089	0.0101	0.0100	0.0101
	(0.0220)	(0.0220)	(0.0220)	(0.0213)	(0.0213)	(0.0212)
tech				0.0329	0.0329	0.0329
				(0.0196)	(0.0196)	(0.0196)
Num. obs.	13599	13602	13599	13599	13602	13599
factor(state)	55	55	55	55	55	55
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.0236	0.0233	0.0236	0.0294	0.0291	0.0294
R^2 (proj model)	0.0125	0.0123	0.0125	0.0183	0.0181	0.0183
Adj. R^2 (full model)	0.0183	0.0181	0.0184	0.0241	0.0238	0.0242
Adj. R^2 (proj model)	0.0118	0.0117	0.0119	0.0176	0.0175	0.0177

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 12: Similar to asian CEOs, both board gender diversity and diversity narrative have an insignificant but negative impact on the election of Indian CEOs. This implies that neither diversity narrative from NYT news nor board gender diversity has anything to do with the election of Indian CEOs. Obviously, boards with diverse nationalities are more likely to elect Indian CEOs. Education and tech industries have a similar impact. A non-technical certification like the CPA definitely does not get an Indian elected as the CEO of a firm. Also, tech industries definitely have higher propensity to elect Indian CEOs.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	-0.0002		-0.0002	-0.0001		-0.0001
	(0.0004)		(0.0004)	(0.0004)		(0.0004)
genderdiv	-0.0071	-0.0067		-0.0059	-0.0055	
	(0.0183)	(0.0183)		(0.0180)	(0.0181)	
nationalitymix	0.0629^{*}	0.0627^{*}	0.0627^{*}	0.0609^{*}	0.0606^{*}	0.0607^{*}
	(0.0267)	(0.0267)	(0.0267)	(0.0249)	(0.0249)	(0.0249)
numberdirectors	-0.0014	-0.0014	-0.0015	-0.0011	-0.0011	-0.0012
	(0.0009)	(0.0009)	(0.0009)	(0.0007)	(0.0007)	(0.0007)
bindep	0.0111	0.0115	0.0115	0.0113	0.0118	0.0116
	(0.0165)	(0.0166)	(0.0164)	(0.0164)	(0.0164)	(0.0163)
age	0.0002	0.0002	0.0002	0.0003	0.0003	0.0003
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
CFA_CEO	-0.0168^{**}	-0.0168^{**}	-0.0170^{**}	-0.0171^{***}	-0.0172^{***}	-0.0173^{***}
	(0.0051)	(0.0051)	(0.0051)	(0.0045)	(0.0045)	(0.0045)
CPA_CEO	-0.0178^{***}	-0.0179^{***}	-0.0178^{***}	-0.0170^{**}	-0.0171^{**}	-0.0170^{**}
	(0.0050)	(0.0050)	(0.0050)	(0.0055)	(0.0055)	(0.0054)
PhD_CEO	0.0291	0.0291	0.0292	0.0299	0.0298	0.0300
	(0.0398)	(0.0398)	(0.0398)	(0.0394)	(0.0395)	(0.0394)
tech				0.0213	0.0212	0.0213
				(0.0231)	(0.0231)	(0.0231)
Num. obs.	13599	13602	13599	13599	13602	13599
factor(state)	55	55	55	55	55	55
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.0295	0.0293	0.0294	0.0309	0.0308	0.0309
R^2 (proj model)	0.0086	0.0085	0.0086	0.0101	0.0100	0.0101
Adj. R^2 (full model)	0.0242	0.0242	0.0243	0.0256	0.0256	0.0257
Adj. R^2 (proj model)	0.0079	0.0079	0.0080	0.0093	0.0093	0.0094

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 13: When Indians and Chinese are considered together in terms of being elected as CEOs, the mix of nationalities on boards has a comparatively lesser impact. Even a coveted CFA certification does not get an asian elected as the CEO, if the pool of candidates consist of Indians and Chinese. If anything, CFA and CPA are definite deterrents of any possibilities of election if Indian and Chinese CEOs. Only hard technical education like a PhD or similar increase the chances of getting an Indian or Chinese elected at the highest levels of firm leadership.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
b_d_diversity	−0.0001		−0.0001	−0.0001		−0.0001
	(0.0003)		(0.0003)	(0.0003)		(0.0003)
genderdiv	−0.0050	−0.0050		−0.0056	−0.0057	
	(0.0085)	(0.0085)		(0.0085)	(0.0085)	
nationalitymix	−0.0051	−0.0051	−0.0052	−0.0039	−0.0039	−0.0041
	(0.0107)	(0.0107)	(0.0107)	(0.0103)	(0.0103)	(0.0103)
numberdirectors	0.0001	0.0001	0.0000	−0.0001	−0.0001	−0.0001
	(0.0006)	(0.0006)	(0.0006)	(0.0005)	(0.0006)	(0.0006)
bindep	0.0125	0.0125	0.0128	0.0124	0.0124	0.0127
	(0.0074)	(0.0074)	(0.0074)	(0.0071)	(0.0071)	(0.0072)
age	0.0005^{*}	0.0005^{*}	0.0005^{*}	0.0005^{*}	0.0005^{*}	0.0005^{*}
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
CFA_CEO	-0.0098^{**}	-0.0098^{**}	-0.0099^{**}	-0.0096^{**}	-0.0096^{**}	-0.0098^{**}
	(0.0030)	(0.0030)	(0.0031)	(0.0034)	(0.0034)	(0.0035)
CPA_CEO	-0.0090^{*}	-0.0090^{*}	-0.0089^{*}	-0.0094^{*}	-0.0094^{*}	-0.0094^{*}
	(0.0040)	(0.0040)	(0.0040)	(0.0041)	(0.0041)	(0.0041)
PhD_CEO	0.0202	0.0202	0.0203	0.0198	0.0198	0.0199
	(0.0189)	(0.0190)	(0.0190)	(0.0195)	(0.0196)	(0.0195)
tech				-0.0117^{*}	-0.0117^{*}	-0.0116^{*}
				(0.0047)	(0.0047)	(0.0047)
Num. obs.	13599	13602	13599	13599	13602	13599
factor(state)	55	55	55	55	55	55
factor(Year)	11	11	11	11	11	11
R^2 (full model)	0.0309	0.0309	0.0308	0.0320	0.0319	0.0319
R^2 (proj model)	0.0045	0.0045	0.0045	0.0056	0.0056	0.0056
Adj. R^2 (full model)	0.0256	0.0257	0.0257	0.0267	0.0267	0.0267
Adj. R^2 (proj model)	0.0038	0.0039	0.0039	0.0049	0.0049	0.0049

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Table 14: But when Chinese CEOs are considered separately, nationality mix in boards does not lead to their election. Education has similar effects on the election of Chinese CEOs per se. However, tech firms are less likely to elect Chinese CEOs. This implies Chinese CEOs are chosen in very specific cases because of idiosyncratic reasons. This is mostly when the firms have Chinese origins. This could also be to gain access to the Chinese market and sell the products or services to the Chinese consumers.