NHH

Norwegian School of Economics
Bergen, Spring 2023

Does including more female board members help corporations to reduce non-compliance?

A study on California's mandatory gender quota

Wendi YI
Supervisor: Evelina.Gavrilova-Zoutman

Master thesis, Economics and Business Administration
Major: Business Analytics
Minor: Economic Analysis

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgments

This thesis is the final piece of my study journey at the Norwegian School of Economics (NHH). In this journey, I experienced a global pandemic, struggled with remote learning, and battled with long winters in Norway. Now I am proud to present this thesis as the drop scene of my Master of Science degree.
I would like to thank my supervisor Evelina Gavrilova–Zoutman for suggestive guidance and discussions throughout the semester. In addition, I appreciate the help of all the staff and administration of the NHH. Lastly, I want to thank my parents and friends for their continued understanding and support.

Norwegian School of Economics

Bergen, Spring 2023

Wendi YI

Abstract

California enacted the law of SB826 in 2018, which mandates corporate boards to include a minimum number of female directors. I study companies' reactions to this gender quota from the perspective of board diversity as well as corporate compliance. My sample encompasses data on the publicly held firms headquartered in California, Arizona, Oregon, Nevada, Texas, or Washington from 2015 to 2021.

I find that compared to companies in the other five states, the companies based in CA enhance female presence in boardrooms markedly after the enactment of the quota. However, with more women in the boards of California corporations, their responses to corporate noncompliance are no different than those of companies situated in the other five states. The findings suggest that including more female board members, in the context of mandatory gender quotas, does not notably help corporations to reduce noncompliance.

Contents

Reference 35

List of Figures

List of Tables

1 Introduction

Gender diversity in boardrooms has long been an attention-gathering topic. In September 2018, California (CA) enacted a gender diversity law (SB 826). It requires publicly traded companies headquartered in California to increase female representation in their boardrooms ("Bill Text - SB-826 Corporations: Boards of Directors." 2018). This law made CA the first state in the US to pass a mandatory gender quota ("Women on Boards," n.d.). In addition, it also created an exogenous shock to board compositions, setting a stage for studying the impact of gender composition on corporate governance in different aspects (Greene, Intintoli, and Kahle 2020).

By exploring relevant data and applying several difference-in-difference causal methods, I try to decipher whether the CA-Quota leads to an increase in board seats for women among CA-based listed companies (*Hypothesis 1*). Then, I investigate whether including more female board members helps to reduce corporations' illegal practices (*Hypothesis 2*).

To address the research questions, I construct a comprehensive panel dataset encompassing 1993 publicly held companies based in California, Arizona, Oregon, Nevada, Texas, or Washington from 2015 to 2021. Companies based in California make up a treatment group, while firms based in Arizona, Oregon, Nevada, Texas, or Washington fill in a control group.

Each observation in the dataset provides information on the percentage of female board members of a given company in a particular year. For the purpose of this research, I define *female index* as the average proportion of board seats offered to women among listed firms in a certain region. The defined female index varies year by year. Furthermore, the dataset also entails information relating to corporate crimes. Since publicly companies may reveal major litigation through current events (8-K) filings[1], I then gather all the 8-K filings submitted by covered companies between 2015 and 2020. A textual analysis is conducted to identify filings containing information about criminal activities. In light of this, a dummy variable that indicates whether a company is involved in illegal practices in a particular year is established and included in the dataset. Consequently, I define the proportion of corporations involved in illegal activities in a given region as *crime index*, which changes annually. Additionally, confounding factors, such as the yearly average number of employees, annual average number of directors, annual revenues, and annual COVID-19 financial assistance, are also adopted in the dataset.

[1] 8-K filings are specific documents submitted by publicly traded companies. Form 8-K is used for current reports under the Securities Exchange Act of 1934. Publicly companies generally disclose major "current events" in 8-K filings.

Based on the dataset attained, I then utilise several difference-in-differences (DID) methods to test the research hypotheses. The analysis begins with a conventional DID approach with a two-way fixed effects framework. Then, it extends to an event study DID to observe the dynamic effects following the quota implementation. Finally, I use a two-stage DID approach as a robustness check.

The study has two key comparisons. The average change over time of the female index in the treatment group is compared to the average change over time of the female index in the control group. Similarly, the mean crime index for treated units is also compared to the mean crime index for untreated units. In addition, the differences between treatment and control groups vary over time. By analysing the differences before the quota's initiation, I examine whether the required common trend assumption is confirmed. By focusing on the differences post-quota, I uncover the possible influences from the quota, providing insights into the potential impacts of gender quota on gender diversity and the impacts of female presence on corporate deviant behaviour.

The results from the DID analysis indicate that no differential pre-trend is presented between treatment and control groups in terms of either the female index or the crime index, thus upholding the parallel trend assumption. In addition, the findings of conventional DID reveal that the CA-based firms experience an overall 2.81% greater increase in the female index than those based in the other five control states at a significance level of 1%. It also suggests an overall 0.46% larger drop in the crime index for the treated units compared to the untreated. But this effect is not statistically significant.

In line with the conventional DID, the event study DID reflects that the mandatory gender quota has an obviously positive effect on the female presence in boards. The average treatment effect for treated units (ATT) on the female index after one year, two years, and three years of exposure to the quota policy is 2.01%, 3.18%, and 6.43%, separately. What's more, the event study DID does not support the efficacy of increasing board diversity in reducing corporate noncompliance. It shows that ATT on the crime index is -0.47%, -0.25%, and -0.85% in the first, second, and third years after the quota came into effect, respectively. However, all of those coefficients are statistically insignificant. That is to say, the event study DID does not find notable changes in the crime index of California's listed businesses after enacting the quota, compared to untreated units.

To deal with potential flaws associated with linear regressions with the two-way fixed effects framework [2], I also employ a two-stage difference-in-difference regression model as a robustness check. The outputs of the two-stage DID align with those of event study DID, thus proving

[2] See Section 4.3

the robustness of the latter.

I also regard the possible impacts of other similar policies. However, these policies or rules under consideration do not overlap with the scope of this study in three dimensions: time, space and effectiveness. To be more specific, those policies: (1) are not in effect during the selected research period (e.g. Nasdque's board diversity rule was approved on December 2022); (2) do not apply to the states included in this study (e.g. New York requires boards to disclose their demographic makeup); (3) are not mandatory; (4) or if they are mandatory, do not carry penalties (e.g. Washington requires either an increase in female board members or disclosure of efforts to comply with the policy and reasons for failing to do so). Hence, the collective evidence supports that no simultaneous policies may influence this study's control or treatment groups. Then, a potential causal explanation can be carried out — the rise in the female index of California-based corporations is likely due to the implementation of the gender quota. However, a higher female presence in boards does not notably reduce the likelihood of corporations being involved in illegal activities.

I discuss the possible reasons behind the result retrieved from the regression models. The outcome may be because that female members are still less present in more influential board positions. Without further promotions to more influential roles, female directors do not fully exert their influence in reducing noncompliance. Besides, gender barriers remain in boardrooms. Those barriers may prevent women members from inhibiting deleterious corporate behaviour. In addition, the insufficient supply of capable female candidates may increase the likelihood of companies hiring less capable female directors to meet mandatory quota requirements. These less competitive appointees may be slack in compliance and therefore do not help to reduce corporate deviant behaviour.

Much theoretical research supports that women are less inclined to commit crimes than men in multiple contexts (see Akers 1991; Steffensmeier and Allan 1996). A number of empirical studies also have uncovered the gender gap in crime (see Campaniello and Gavrilova 2018). Following the enactment of SB 826, empirical works related to it have emerged. Most of them focus on the market reactions to the quota. Few studies had explored the possibility of mitigating corporate criminal tendencies through the mandatory gender quota (see Greene, Intintoli, and Kahle 2020; Gertsberg, Mollerstrom, and Pagel 2021; Allen and Wahid 2023). This paper examines the impact of board diversity on corporate compliance in the context of exogenous shocks caused by the quota. Contrary to theoretical expectations or previous empirical research, I do not find evidence supporting the causal relationship between female presence in boards and corporate compliance. Through that, I contribute to understanding whether (or to what extent) including more women in boards may influence corporate compliance and call for further research on the relationship between gender representation and corporate compliance in different contexts.

2 Background

2.1 Gender Quota in California

In September 2018, California Senate passed a bill (SB 826). This bill makes an effort to increase board diversity by announcing that publicly held companies headquartered in California should include a certain number of females in their boardrooms, or face fines.

The CA-quota is deployed in two phases. Phase 1, announced in September 2018, required CA-based listed companies to include at least one woman on their boards by the end of 2019. Phase 2 further mandated those companies to offer more board seats to females based on the total number of board members by the end of 2021. More specifically, companies with five board members should have at least two females; companies having six or more board members should contain no less than three women in boardrooms; companies with no more than four board members should continue to comply with the Phase 1 requirement. Covered corporations that do not meet the substantive gender representation requirements or fail to provide board member information to the California Secretary of State may face a fine of $100,000. For repeated offences, the penalties can range from $100,000 for the first offence to $300,000.[3]

The law also encountered opposition. In December 2022, the Superior Court of California invalidated the gender diversity law, which effectively stopped the quota's enforcement. As the case is currently under appeal, the future of SB 826 remains uncertain (Posner 2022).

2.2 Practices in Other States or Agencies

A rising interest in promoting board equity through mandatory or voluntary measures springs across states in the US, with varying methods and enforcement mechanisms ("Will More States Set Board Diversity Mandates?" 2020).

Washington added a new board diversity rule to the Washington business corporation act. The new rule mandates each public corporation to have a gender-diverse board of directors by January 1, 2022. Alternatively, companies that fail to do so must disclose information regarding their approach to developing and maintaining board diversity ("RCW 23B.08.120," n.d.).

[3]Source: SB-826 Corporations: boards of directors. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB826

Board diversity legislation closely mirroring CA's SB826 is in progress in Michigan and New Jersey (Helwig, n.d.). Maryland, New York, and Illinois require firms to disclose their board compositions, while Ohio encourages voluntary disclosure ("Will More States Set Board Diversity Mandates?" 2020).

The Nasdaq has also adopted a diversity rule that requires companies listed on its US exchange to meet its board diversity objective or provide explanations, as well as disclose company-level board diversity data annually ("Board Diversity Disclosure Five Things" 2023). Securities Exchange Commission (SEC) approved it on December 2022.[4] Also, similar policies have been rapidly emerging from a variety of other investment firms and regulatory agencies, including the SEC, Goldman Sachs, and Institutional Shareholder Services, Inc. (ISS) ("Will More States Set Board Diversity Mandates?" 2020).

2.3 Relevant Studies

Many empirical works also investigate the relationship between employment diversity and corporate compliance. Baum, Gafni, and Lazar (2022) study 660 public corporations traded on the Israeli Tel-Aviv Stock Exchange from 2005 to 2017, suggesting that increasing female representation in boards reduces corporations' criminal tendencies. By investigating US accounting or auditing fraud sample observations from 2011 to 2021, Maulidi (2022) find that among non-state-owned enterprises, "female corporate leaders are less likely to engage in corporate fraud", and firms with greater female representation in boards experience fewer fraud cases. In contrast to the above findings, McLaughlin et al. (2021) use a dataset including all firms in the UK that "were investigated by the Financial Reporting Council through the audit enforcement procedure from 2014 to 2019" and find female representation does not significantly influenced the likelihood of corporate scandal.

Though California's gender quota has a relatively short life span, studies have captured an increase in the number of women occupying board seats in California post-quota. Besides that, Greene, Intintoli, and Kahle (2020) examine a negative reaction from the stock market, arguing that firms may suffer less severe negative influence from the mandatory gender quota if they are more attractive to female candidates or in an industry with a more excellent supply of female candidates. In a similar context, Gertsberg, Mollerstrom, and Pagel (2021) analyse shareholders' attitudes towards female board appointees and concludes that the adverse reaction from the stock market is mainly driven by firms failing to "turn over their

[4] Source: SECURITIES AND EXCHANGE COMMISSION (Release No. 34-96500; File No. SR-NASDAQ-2022-075) https://www.sec.gov/rules/sro/nasdaq/2022/34-96500.pdf

least-supported male directors". Allen and Wahid (2023) provide evidence that there is no discernible decline in the quality of newly appointed female director after the implementation of SB826 "either relative to pre-regulation appointments or to male director appointments".

3 Data

The data used in the study comes from three different sources. I attain company-level information from Compustat and BoardEx databases. From Compustat, I obtain multi-dimensional data on individual companies, while from BoardEx, I gather data about board members. In the absence of an available legal database subscription, I collect litigation information from relevant 8-K filings submitted by public firms to the EDGAR[5]. From those relevant 8-k filings, I examine legal issues experienced by sampled companies during the selected period. Considering the immense influence that the COVID-19 pandemic has on corporate governance, I also collect relevant COVID-19 data from USASpending[6].

Selecting targeted companies and period

The sample data includes listed firms affected by the CA-quota. In addition, I also adopt publicly traded companies headquartered in the states of Washington (WA), Arizona (AZ), Oregon (OR), Nevada (NV), or Texas (TX) as counterparts of California-based public companies. Among all selected states, Oregon, Nevada, and Arizona are adjacent to California; Washington State is on the West Coast[7] where California is located as well; Texas is the second largest economy in the United States[8] and one of California's main competitors[9]. By doing so, this study covers states that are either in the same region as California or may have business environments and trends that are comparable to those of California. Thus, I narrow down the likelihood that factors other than treatment (in this case, the CA-quota) would lead to different outcomes in the treatment and control groups.

California's gender quota was enacted in September 2018 and temporarily nullified in December 2022. Hence, I observe the changes in the female index and crime index for the three years following 2018, as some of the selected companies have not yet published their annual reports for 2022. Consequently, I also use the data from three years prior to 2018 to test the common trend assumption of DID method. In other words, the time span of this study is symmetrical, from 2015 to 2021.

[5]The full name of EDGAR is Electronic Data Gathering, Analysis, and Retrieval system (EDGAR). EDGAR is maintained by SEC. All publicly companies registered in the USA are required to file specific forms electronically through the system. Available on : <https://www.sec.gov/edgar>

[6]An official website of the US government. https://www.usaspending.gov/

[7]United States Census Bureau defines that West Coast (Pacific Coast) includes Alaska, California, Hawaii, Oregon, and Washington. https://www2.census.gov/geo/pdfs/maps-data/maps/reference/us_regdiv.pdf

[8]Source: Gross Domestic Product by State and Personal Income by State, 4th Quarter 2022 and Year 2022 published by the US Bureau of Economic Analysis. https://www.bea.gov/sites/default/files/2023-03/stgdppi4q22-a2022.pdf

[9]Gross Domestic Product by State and Personal Income by State, 4th Quarter 2022 and Year 2022 published by the US Bureau of Economic Analysis denotes that California is the largest economy in the US, while Texas is the second largest.

In Section 2.2, I discuss several ongoing policies in the US that may impact the results of this study. However, I do not observe similar policies being implemented in Arizona, Oregon, Nevada, and Texas from 2015 to 2021. In contrast, a mandatory gender quota was introduced on June 11, 2020, in Washington. Washington's quota requires publicly traded companies headquartered in the state to have a gender-diverse board of directors by January 1, 2022. Unlike companies in California, affected companies in Washington are offered an alternative to disclosing information regarding their approach to developing and maintaining diversity on boards. Thereupon, I conduct a $t-test$ to determine if the female index in Washington in 2021 was significantly higher than that in 2020. The alternative hypothesis is that the true difference in means is greater than zero. The resulting p-value of 0.97 (>0.05), however, means the null hypothesis is not rejected, indicating that the female index of Washington is not significantly higher in 2021 than in 2020. Thus, including Washington in the control states does not compromise the accuracy of this study.

From the three dimensions of time, space, and simultaneous policies, I ensure that California's gender quota is the most likely source accounting for potential differences between treatment and control groups post-quota. Figure 1 shows the location of each state and the number of sampled firms of each state covered by this study.

Tracking the changes in female index

In order to reflect the changes in the female index, from the database BoardEX I obtain data for each company on the number of directors per year and the proportion of male board members among all board members per year. I also created a transformed variable, $1 - the\ percentage\ of\ male\ board\ members$, to explicitly express the annual proportion of female board members for each company. In this way, I am able to draw from the data the changes in the level of female board members of the company over the years.

In Figure 2, I observe female index increased from 2015 to 2021 both in California and in the other five control states as a whole. In 2015, the female index of California-based public companies was 10.76%, similar to the female index (10.18%) of the control group. This similarity continued to 2018, in which the year CA sustained the female index of 15.30% while the control group 13.45%. From 2018, California's female index rose sharply. However, the female index developed in the control group aligned with its original trend. Till 2021, California enjoyed a female index of 30.4%, which is around 1.5 times higher than that (20.57%) of the control group. Though the female index for California and the female index for control states have a more or less similar upward trajectory between 2015 and 2017, the potential parallel trend between these two groups prior to 2018 is further tested in Section 5.

Measuring crime index with 8-K filings

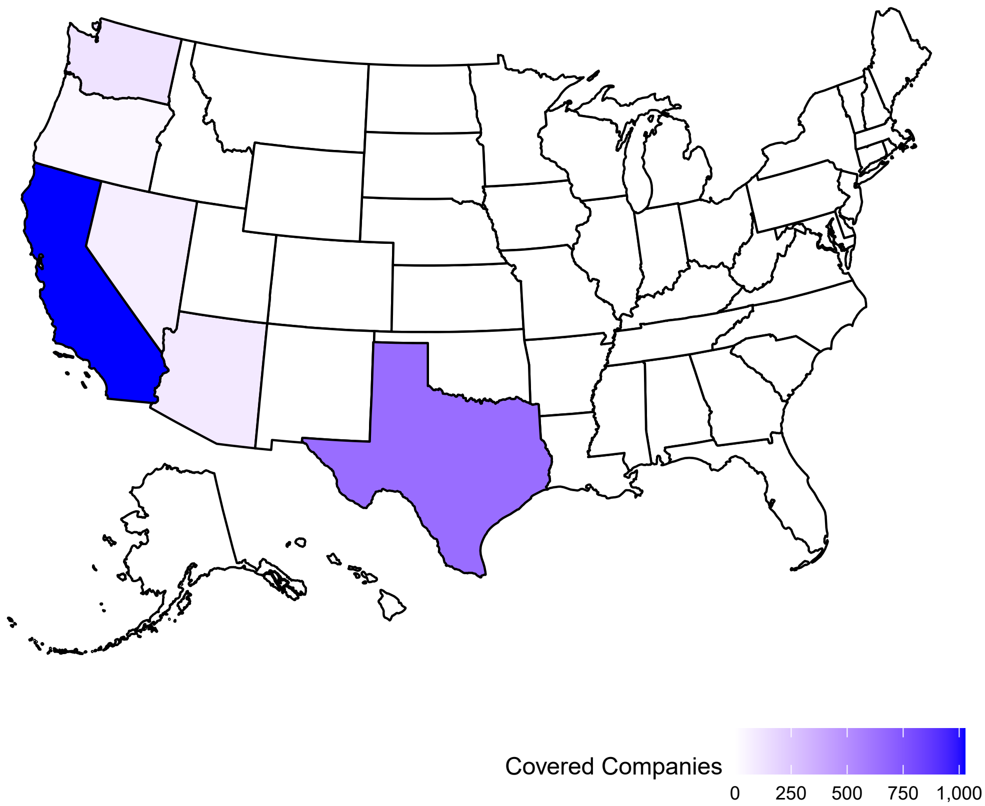

Figure 1: *Coverage of Treatment and Control Groups.*

Notes: The figure reflects the number of companies entiled in this study by state. A darker color indicates more companies are coverd by this study in a state. 1025 public companies have their headquarters in CA, and 120 in WA, 94 in AZ, 34 in OR, 73 in NV, and 647 in TX. The data of US map comes from a R package of "usmap", which follows the newest "Cartographic Boundary" publised by the United States Census Bureau.

Firms may positively engage or passively be involved in various types of legal violations. Such activities, if disclosed, "can result in major sanctions imposed by the US Department of Justice, the Federal Trade Commission, and/or the Securities and Exchange Commission"(Williams, Fadil, and Armstrong 2005). These institutions all have databases or websites to make corporate criminal records accessible.[10]

Among those databases, SEC's EDGAR system is an important source for learning about illegal issues listed firms have experienced. Public corporations are required to self-disclose major legal activities against themselves by submitting specific filings to EDGAR. Companies may reveal major litigation through current events (8-K) filings, otherwise in the legal

[10]DOJ maintains National Archive of Criminal Justice Data (NACJD), available on https://bjs.ojp.gov/data. Federal Trade Commission has a library of cases and proceedings, available on https://www.ftc.gov/legal-library/browse/cases-proceedings. Securities and Exchange Commission maintains EDGAR system, available on https://www.sec.gov/edgar.

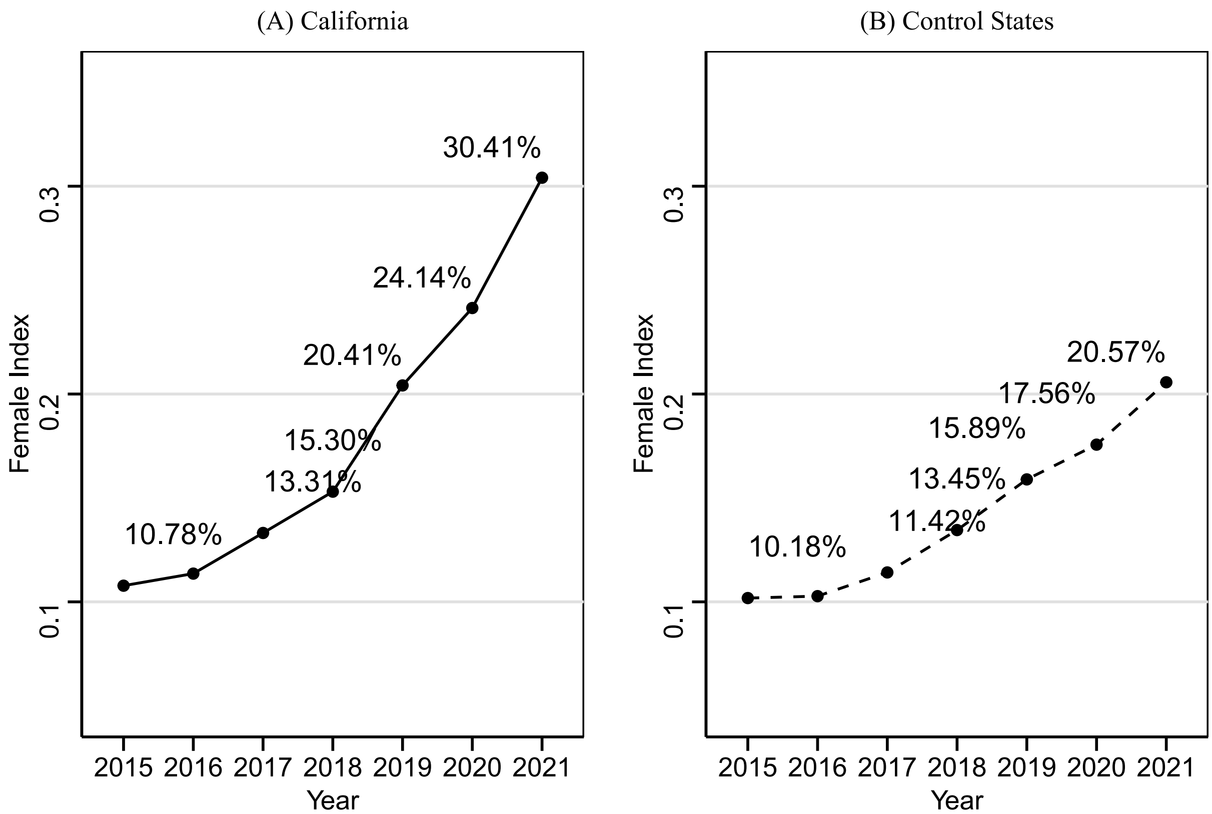

Figure 2: *The Development of Female Representation in Boardrooms.*

Notes: In this study, the female index is defined as the average proportion of female board members of listed companies in a particular region. I use this index to approximate regional representation of women in boardrooms. California is the treatment group, while Arizona, Oregon, Nevada, Texas, and Washington make up the control group. Plot A presents female index of CA-based companies. The index increases from 10.78

proceedings section of quarterly (10-Q) or annual (10-K) filings.

I first use an R function, *getFilings*[11], to download all 8-K filings relevant to sampled companies. Furthermore, I retain 8-K reports containing manually selected keywords (Appendix A) that indicate a company might have been involved in corporate crimes. When processing textual information of those 8-K filings, several regular expressions are adopted to exhaust as many reasonable keyword combinations as possible to improve the accuracy of crime content detection. The textual analysis returns a list of 8-K filings preserving at least one of the keywords or keywords combinations, as well as the publication date and company name for each document.

Thus, after grouping the obtained list by year and company, I summarise the total number of

[11]This function comes from R package edgar. It is a tool for the US SEC EDGAR retrieval and parsing of Corporate Filings. https://cran.r-project.org/web/packages/edgar/index.html

legal cases for each firm in each year. In light of this, I establish a binary variable to highlight whether a corporation is likely enmeshed in legal disputes in a particular year. Among 1993 sampled companies, 232 are identified as involved in corporate crimes. Figure 3 shows that from 2015 to 2021, the crime index of California and that of control states fluctuate between 2% and 4% approximately. Raw data does not present an apparent parallel trend between treatment and control groups pre-quota, which is further discussed in Section 5.

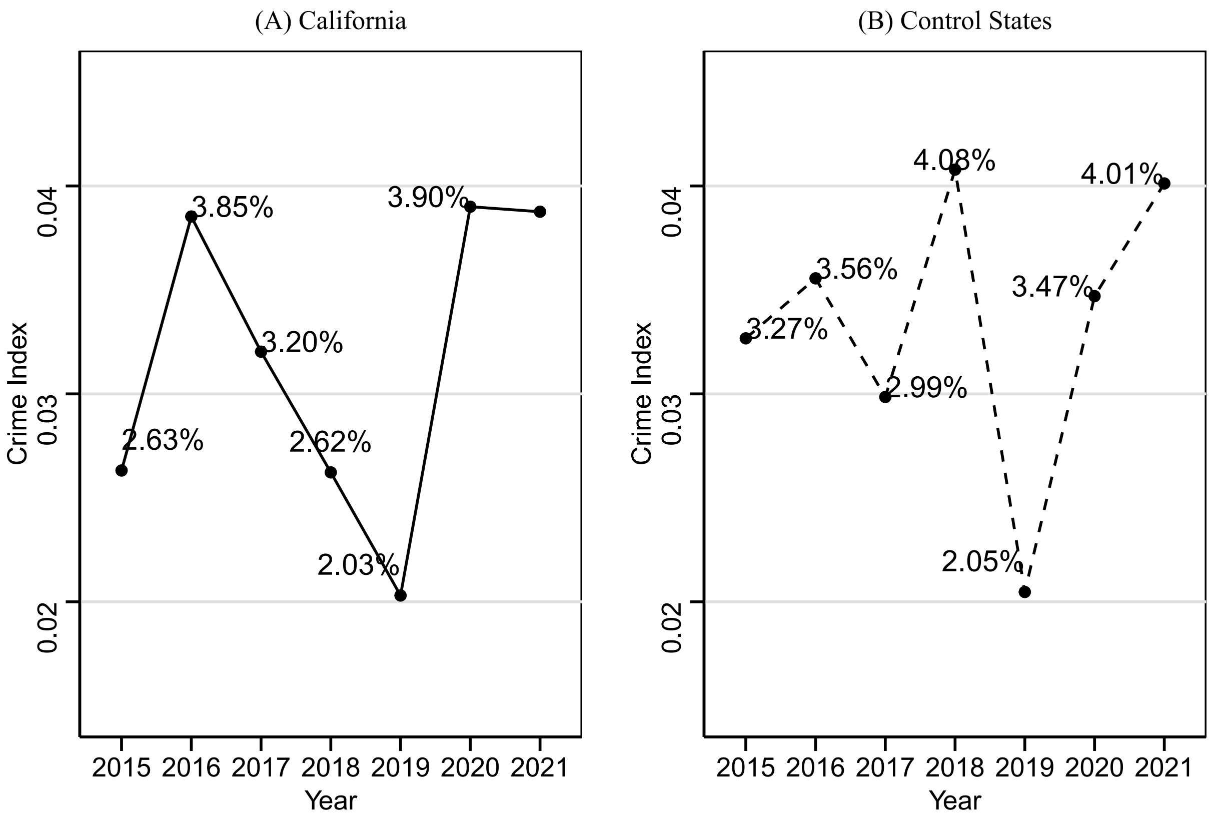

Figure 3: *The Development of Crime Index in Different Regions.*

Notes: In this study, the crime index is defined as the proportion of listed companies in a particular region that are likly enmeshed in legal disputes. The crime index flucates year by year. I use this index to approximate crime tendencies of corporations in a region. Panel A presents crime index for CA-based companies from 2015 to 2021, while Panel B shows crime index for listed firms based in control states in the same time period. In 2018 around 2.63% CA-based public companies were engaged in illegal violations. At the same time, approximate 3.27% public companies based in control states were engaged in illegal issues.

Quantifying affections of the COVID-19 pandemic

Notably, a collection internal and external factors influences whether a business carries out an illegal activity. When the CA Quota took effect, an outbreak caused by COVID-19 dominated the world's attention. Governments worldwide have implemented many different emergency stimuli or financial assistance programs to sustain their economies ("The Impact of COVID-19 on Organized Crime" 2020). Those economic recovery schemes consequently increase the supply and availability of government funds. It then increases the risk of fraud through fraudulent claims, misappropriation of funds and corruption as these funds get redirected to corruption (Ahern 2017).

The US government has launched multiple COVID-19 funding schemes. Each scheme offered either money or contracts to different types of recipients. Recipients can be individuals, organisations, companies or different levels of local governments. Among all the fundings, overall financial assistance awards possess the vast majority of spending related to COVID-19 ("COVID Relief Spending," n.d.). From the topic page "COVID-19 Spending" of the site "USASpending", I collect data on city-level aggregated financial assistance awards from 2019 to 2021. I use the logarithm of the awards to simulate the impacts or lures that companies in a given city may face during the pandemic.

Constructing other control variables

Several factors that may influence either the female index or the crime index are identified and included in the model as control variables.

Prior theoretical and empirical works support including firm size as a control variable, as it has an influence on illegal activities within firms (Daboub et al. 1995; Johnson, Daily, and Ellstrand 1996; Williams, Barrett, and Brabston 2000). Firm size is measured as the logarithm of yearly sales (in million) during the study period. I also include a control variable reflecting the annual employee of firms, which is also measured as the logarithm of the yearly number of employees (in thousand).

Some organisations are, however, sliced out due to a lack of information on one or more company-level variable(s) selected by this research. Hence, I construct a panel dataset containing only the companies with completed information and headquartered in selected states from 2015 to 2020. It is worth noting that the dataset is unbalanced as companies may move out of six chosen states or be delisted in the research period. Finally, the dataset includes 1993 companies scattered across 62 different industries. 1025 companies have their headquarters in CA, and the rest firms are based on WA (120), AZ (94), OR (34), NV (73), or TX (647).

4 Empirical Methods

To detect the influence that CA's quota or board diversity may bring on public firms, I test two hypotheses:

Hypothesis 1*: California's gender quota significantly increases board seats for women in covered companies.*

Hypothesis 2*: Increasing female presence on boards significantly decreases corporate criminal tendencies in covered companies.*

I first conduct a static DID regression model with two way fixed effects (TWFE) framework to examine possible causal effects of the quota on the change in female gender representation on boards (i.e. hypothesis 1) and on the change in corporate criminal behaviour (i.e. hypothesis 2) in CA-listed companies before and after the quota. Instead of only looking into aggregated before-and-after treatment effects, I also expect to present dynamic dis-aggregated treatment effects. Therefore, I use an event study DID to estimate evolvements of treatment effects over time.

The validity of the parallel trend assumption is tested in advance. If the assumption is held, then there would be non-significant differences between treatment and control groups before the event (in this case, the quota). An event study is able to capture the pre-treatment differences and then be used to test whether the assumption is valid.

As one of the remedies to criticism for the two-way fixed effects framework, John Gardner developed the two-stage DID method. I also include two-stage DID models as a robustness check for conventional and dynamic DIDs.

4.1 DID with Two Way Fixed Effects

This research starts from a conventional DID model. The model compares changes in female index between CA-based companies and the rest and also changes in crime index between the two groups. The key regressor in the model is the dummy variable $post_{it}$ that equals 1 if the quota policy applies to $company_i$ in $year_t$; otherwise 0. $post_{it}$ always equals 0 for a company that is not bounded by the quota during all sample period. The conventional DID regression model adhere to the following form:

$$Y_{it} = \beta * post_{it} + \alpha_i + \theta_t + \Gamma * X_{it} + \varepsilon_{gt} \tag{1}$$

α_i is the company fixed effect; θ_t is the time fixed effect; X_{it} are time-varying control variables, and coefficients of those variables are recorded by Γ.

What's more, β is the DID estimate. Y_{it} is the outcome. When the outcome is female presence, then Y_{it} is the percentage of female board members of $company_i$ in $year_t$. In this case, β is expected to be positive. Because the positive estimate of β suggests that the CA-quota does help to increase the number of females included in boards. In contrast, if the outcome represents corporate legal violations, then Y_{it} will be a binary variable. It equals 1 if $company_i$ is involved in illegal practices in $year_t$; otherwise 0. In this situation, β is desired to be negative, as it is hoped that the increased presence of women on boards helps to reduce the companies' propensities to engage in illegal activities.

Lastly, standard errors,ε_{gt}, are clustered by $industry_g$ where $company_i$ belongs to.

4.2 Event Study DID

Unlike the conventional DID that summarizes the overall before-and-after treatment effects, event study DID take the dynamic of treatment effect and variable treatment timing into account by recording year-by-year treatment differences separately. Even though the treatment time is static in this case (i.e. at 2018), this research is still benefit from an event study to observe a fairly dynamic post-event effect of the police. The event study regression model in this research follows the form:

$$Y_{ik} = \sum_{k=-3}^{-2} \zeta_k * post_{ik} + \sum_{k=0}^{3} \zeta_k * post_{ik} + \delta_i + \eta_k + \Upsilon * X_{ik} + \mu_{gk} \tag{2}$$

$post_{ik}$ is a dummy variable, equaling 1 if $company_i$ is influenced by CA-quota at the $k-th$ year before (or after) the event year; otherwise 0.

$k = 0$ means the year that the event takes place; $k = 1$ is the first year after the event year; $k = -1$ is the first year prior to the event year. In other words, $k < 0$ represents pre-event periods, while $k > 0$ records post-event periods. In this study, the event year is 2018. Therefore, the year of 2017 (i.e. $k = -1$) is dropped to avoid perfect collinearity and then is used as the base category.

ζ_k is a point estimate for treatment effect to $company_i$ in $k - th$ year leading (or lagging) the year of the event. Besides, δ_i is a company fixed effect; η_k is a time fixed effect; X_{ik} are time-varying control variables and Υ documents coefficients of those variables. The standard errors, μ_{gk}, is clustered by $industry_g$ that $company_i$ is in.

Y_{ik} is the outcome of $company_i$ in $k-th$ years leading or lagging initial treatment year. The outcome is either the share of board seats offered to females or the dummy variable indicating whether the company is involved in illegal activities.

4.3 Two-Stage DID

It has been demonstrated that running linear regressions using the two-way fixed effects framework has the potential to not correctly reflect an average treatment impact and to be quite misleading in cases of treatment effect heterogeneity (Borusyak, Jaravel, and Spiess 2021; Goodman-Bacon 2021; Chaisemartin and D'Haultfœuille 2020; Sun and Abraham 2021).

Therefore, to remedy this potential flaw, Gardner (2022) proposes the two-stage estimation framework as an alternative approach. In the first stage estimation, group and period effects are identified from the sub-sample of not-yet-treated observations. In the second stage, I get adjusted outcomes by removing the estimated group and period effects from original outcomes. Then average treatment effects are identified by comparing the adjusted outcomes of treated and those of untreated. For untreated units, the value of adjusted outcomes should be close to zero. For treated units, the value of adjusted outcomes should be close to the true treatment effects.

Following the two-stage estimation procedure, I first estimate company fixed effect λ_i, year fixed effect ϕ_t, and covariates X_{it} using the sub-sample of untreated units.

$$Y_{ik} = \lambda_i + \phi_k + *X_{ik} + \mu_{gk} \tag{3}$$

Then I obtain adjusted Y_{it} by removing estimated λ_i, ϕ_t, and covariates from it.

$$\tilde{Y}_{ik} = Y_{ik} - \tilde{\lambda}_i + \tilde{\phi}_k - \tilde{X}_{ik} \tag{4}$$

Finally, I estimate $\tilde{Y}_{it}$ on DID indicator $post_{ik}$ in the hope that τ_{ik} reflects the true treatment effect.

$$\tilde{Y}_{ik} = \tau_{ik} * post_{ik} + \mu_{gk} \tag{5}$$

5 Results

5.1 Analysis on the Changes in Board Diversity

DID Estimations (I)

In this section, I test hypothesis (1) to examine whether there is an increase in the female index among firms headquartered in the treatment state compared to firms in the control states. In addition, if such an increase is observed, whether this increase is linked to CA's quota policy.

Table 1 presents estimates obtained from regression models where the dependent variable is the share of board seats offered to females. For base DID model (column (1)), the only independent variable is the treatment ($post_{it}$) with controlling on the company fixed effect and year fixed effect. This specification removes time-invariant company features and time shock that may affect across all units. For the rest specifications, two company-year level controls (annual employee number and annual sales) and one city-year level control (annual COVID Award) are added to mitigate possible omitted variable bias.

All the specifications present significant positive results, indicating that listed companies in CA enjoy a higher increase in the female index after the enactment of the gender quota. For instance, static DID shows that at the 1% significant level, CA's public companies sustain a 2.81% higher increase in board diversity in the treatment period than companies in control states. In other words, after the quota came into effect, the average 2.81% higher proportion of female board members in CA-based publicly traded firms is observed. Consistent with the static DID, the event study also suggests a significant increase in CA's average female index in each year of the treatment period. Instead of an overall positive average treatment effect, I observe a dynamic treatment effect year by year. For example, after one year of exposure to the quota policy, treated companies obtains an average 2.01% higher female index than companies in the control group; after three years, the treatment group obtains a 6.43% higher female index.

Table 1: *Differences in Women Presence in Boards*

Model:	Base DID (1)	Static DID (2)	Event Study DID (3)	Two Stage DID (4)
$\text{Post}_{i,t=1}$	0.0303***	0.0281***		
	(0.0050)	(0.0047)		
$\text{Post}_{i,k=-3}$			-0.0091*	-0.0023
			(0.0049)	(0.0023)
$\text{Post}_{i,k=-2}$			-0.0031	0.0008
			(0.0034)	(0.0012)
$\text{Post}_{i,k=0}$			-0.0050	-0.0003
			(0.0036)	(0.0016)
$\text{Post}_{i,k=1}$			0.0201***	0.0250***
			(0.0059)	(0.0042)
$\text{Post}_{i,k=2}$			0.0318***	0.0364***
			(0.0062)	(0.0047)
$\text{Post}_{i,k=3}$			0.0643***	0.0662***
			(0.0093)	(0.0077)
Employees		0.0164*	0.0128	
		(0.0098)	(0.0104)	
Sales		0.0058***	0.0043**	
		(0.0017)	(0.0018)	
COVID Award		-0.0003	0.0005	
		(0.0008)	(0.0008)	
Company FE	Yes	Yes	Yes	No[1]
Year FE	Yes	Yes	Yes	No[1]
Observations	8,972	8,971	8,971	8,480
R^2	0.80831	0.80927	0.81359	0.06961
Adjusted R^2	0.75335	0.75450	0.75989	0.06906

Clustered (Industry[2]) standard-errors in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: [1]. In two-stage DID, the fixed effects are included in the first stage model but not the second stage. Only the second stage's outputs are presented in the table. [2]. All units scatter across 62 differnt industries. The dependent variable in all regressions is the percentage of board seats offered to women. In the table, Employees means logarithm transformed yearly average number of employees. Sales is logarithm transformed yearly revenues. COVID-19 Award is logarithm transformed yearly financial assistance received from multiple COVID-19 funding schemes. A series of Post variables are dummies, representing wthether company$_i$ is bounded by California's gender quota in a certain year k or a period t. Specifically, k means $k-th$ year leading or lagging the implementation of the quota, and the values of k range from -3 to 3. t stands for certain periods. $t=0$ is the per-treatment period while $t=1$ is the post-treatment period. For base DID and static DID, excluded category is Post$_{t=0}$. For event study DID and two-stage DID, excluded category is Post$_{k=-1}$. An estimation includes company fixed effect and year fixed effect where noted with "Yes".

The pre-treatment effect presented in column(3) also demonstrates a pre-event parallel trend between treatment and control groups, as all coefficients are not significantly different from zero. The two-stage DID also presents a similar trend, thus upholding the robustness of the results obtained from event study DID. Figure 4 visually presents the evolution of the female index. Each point estimate documents the difference in the female index between treated and non-treated companies in the corresponding year. The baseline used for comparison is their difference in 2017. The female index develops almost horizontally during pre-treatment period, again supporting the validity of parallel trend assumption. A steep rise in the female index after 2018 is noticed. It endorses that CA's gender quota has a significant positive influence on the boards diversity. Along with the higher requirements of Phase 2, a slightly sharper increase in 2021 is recognized, as the end of 2021 is the deadline for meeting the Phase 2 quota. It further visually supports the solid link between the gender quota policy and gender diversity on boards.

Heterogeneity Analysis on Subgroups (I)

The treatment effect across different groups is also of interest to this study. I observed that some of the covered companies had already worked to increase their female board members before the quota took effect. Therefore, it is possible to reason that quota-affected companies can be divided into two subgroups. One subgroup consists of companies that have completed the requirement before the quotas' inure date, named as "pre-fulfill"; and the other one is comprised of companies that have not yet completed the clause's requirement in advance, named as "not pre-fulfill".

Based on this setting, I employ a heterogeneity test to tell whether the quota affects each subgroup heterogeneously and whether subgroups react to the quota differently. In particular, I define companies that meet the quota in advance as those companies that include at least

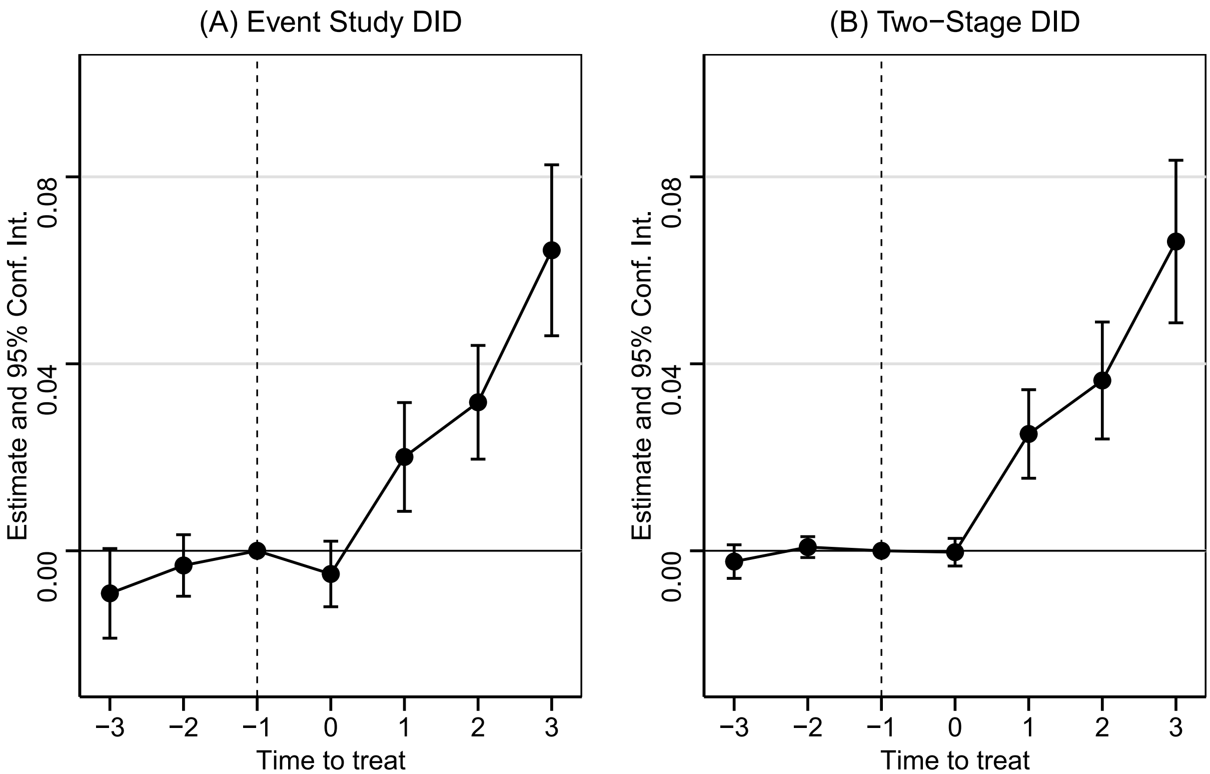

Figure 4: *Disaggregated Treatment Effects on Female Representation in Boards.*

Notes: Both graph (A) and (B) display how the difference in female index between treated and untreated units evolve, while (A) uses outputs from event study DID and (B) from two-stage DID. Each point refers to the difference in corresponding year. Each error bars shows the 95% confident interval of point estimates. X-axis shows the relative timing of the event initiation. 0 is the year of initiation (i.e. 2018), -1 is the year before 2018 (i.e. 2017), 1 is the year after 2018 (i.e. 2019), and so on. The difference in year 2017 is the baseline for comprision.

one female board member (i.e. the phase 1 obligation) for no less than two consecutive years backward from and including 2018. That is to say, if a company adopt one or more female board members in both 2018 and 2017, then that company would be defined as a "pre-fulfill" company; if a company has a male-exclusive board in 2017 or in 2018, it then would be defined as a "not pre-fulfill" company. All pre-fulfilled companies (351) in California consist one sub-treatment group, while the rest in CA (674) belong to the other sub-treatment group.

When estimating for one sub-treatment group, the other sub-treatment group is excluded from the sample, while the control group remains unchanged. Thus the heterogeneous estimation can be compared between two subgroups under the same circumstance. As shown in Figure 5, the "pre-fulfill" subgroup experiences a minor increase in board diversity than the other subgroup does in the treatment period. In 2018, the difference in female index between two subgroups is not statistically different. However, after 2018, female index of “not pre-fulfill” group climb up rapidly and is significantly higher than that of “pre-fulfill” group. The obvious positive treatment effect on “pre-fulfill” group is not observed until 2021, as the end of 2021 is the deadline for completing the requirements of phase 2.

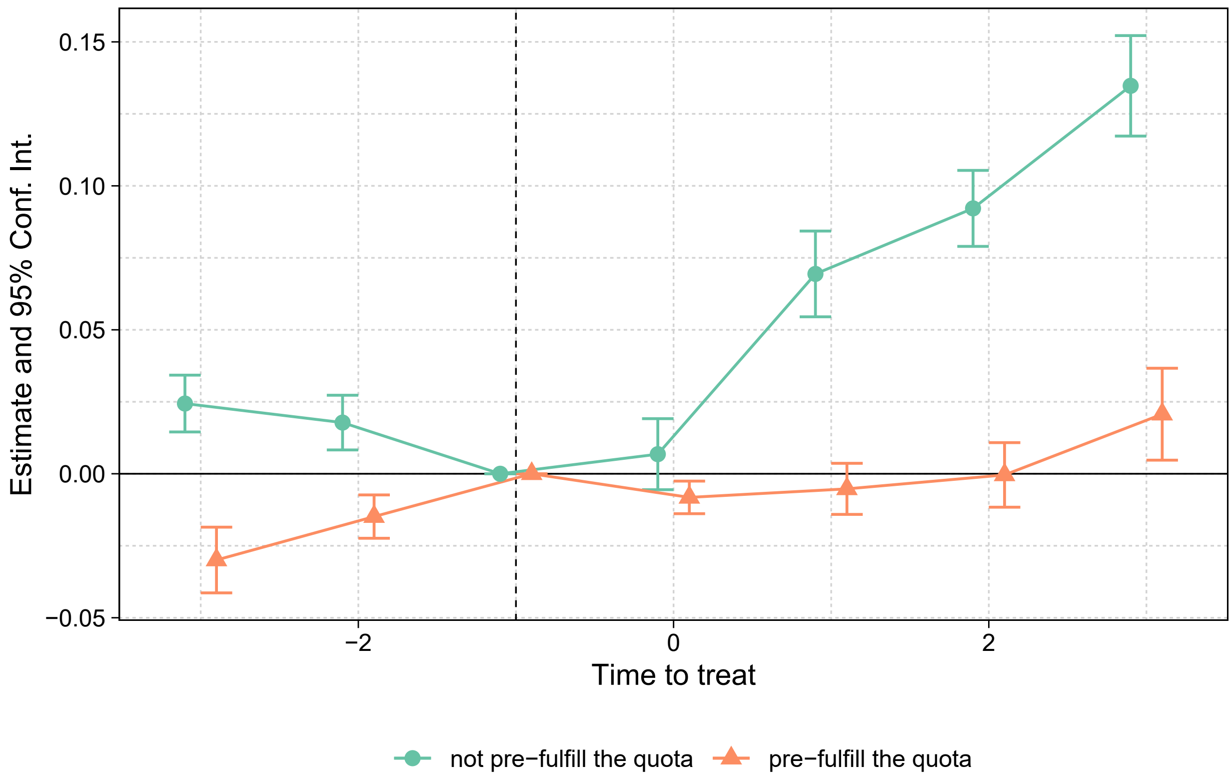

Figure 5: *Disaggregated Effects on Different Subgroups (I).*

Notes: The figure depicts how the differences in female index evolve across subgroups. Each green point refers to the difference in female index between "not pre-fuifill" sub-treatment-group and control group in corresponding year. Green error bars represent the 95% confidence intervals for respective green points. Each organge triangle points out the difference in female index between "pre-fuifill" sub-treatment-group and control group in corresponding year. Orange error bars display the 95% confidence intervals for respective orange points. X-axis shows the relative timing of the event initiation. 0 is the year of initiation (i.e. 2018), -1 is the year before 2018 (i.e. 2017), 1 is the year after 2018 (i.e. 2019), and so on. The difference in year 2017 is the baseline for comprision.

This interesting outcome may be explained by the possible reactions to the quota from each subgroup. Companies that have already met the requirements of the first phase of the quota can either continue to increase the number of female board members in preparation for the upcoming second phase or maintain the number of female board members at this stage for the time being. In contrast, companies in the other subgroup might have a more pressing need to add female board members as they had not included at least one female in their boards yet and then have a relatively short buffer time for phase 2. In fact, the estimates also point out that "not pre-fulfill" group maintains a sharper increase in the female index post-quota. Another explanation is from the perspective of the available qualified women candidates. The assumption behind the explanation is that the pool of qualified female candidates is limited. In contrast to "not pre-fulfill" group, "pre-fulfill" companies may have exhausted their available female candidates. Therefore, it is difficult for them to add more women board members in a relatively short time period.

This difference between the two subgroups also inspires investigation into their difference in criminal propensity, which is discussed in Section 5.1

5.2 Analysis on the Change in Corporate Compliance

DID Estimations (II)

Since the evidence that a significant increase in board diversity among CA's listed companies is presented in the previous sections, I further test hypothesis 2 to express whether including more women on boards will decrease corporate deviant behaviors. Table 2 presents estimates obtained from regression models where the dependent variable is a dummy indicating whether a company is involved in corporate criminal activities.

The reflections of regression models are mixed. When only controlling the company fixed effect and year fixed effect, column (1) denotes an overall 0.12% higher increase in the crime index of CA companies than that of control companies post-event. After adding four control variables, the static DID model (column (2)) reflects a 0.46% decrease in crime index in the treatment group after the policy initiation. Although this coefficients are negative as expected, it is not statistically significant. Regarding of the dynamic treatment effects, event study DID (column (3)) also captures negative point estimates in each year of post-quota period. However, all of them is statistically insignificant. In other words, I do not observe a notable decrease in the number of companies involved in criminal activities after the quota's implementation. As a robustness check, the two-stage DID provides similar results, supporting the robustness of event study DID's outputs. Visually presented by Figure 6, these two regression models also prove a non-differential pre-treatment effect between treatment and control groups. It offers evidence for the validity of the parallel trend assumption, providing support for the feasibility of DID regressions.

Table 2: *Differences in the Number of Companies involved in Illegal Practises*

Model:	Base DID (1)	Static DID (2)	Event Study DID (3)	Two Stage DID (4)
$\text{Post}_{i,t=1}$	0.0012	-0.0046		
	(0.0092)	(0.0087)		
$\text{Post}_{i,k=-3}$			-0.0077	-0.0010
			(0.0105)	(0.0035)
$\text{Post}_{i,k=-2}$			-0.0060	-2.98×10^{-5}
			(0.0146)	(0.0042)
$\text{Post}_{i,k=0}$			-0.0168	-0.0149
			(0.0115)	(0.0108)
$\text{Post}_{i,k=1}$			-0.0047	-0.0023
			(0.0109)	(0.0082)
$\text{Post}_{i,k=2}$			-0.0025	-0.0003
			(0.0118)	(0.0082)
$\text{Post}_{i,k=3}$			-0.0085	-0.0012
			(0.0169)	(0.0145)
Employees		0.0697***	0.0694***	
		(0.0219)	(0.0219)	
Sales		-0.0086	-0.0089	
		(0.0061)	(0.0063)	
COVID Award		-0.0009	-0.0005	
		(0.0015)	(0.0015)	
Number of Directors		0.0058**	0.0058**	
		(0.0028)	(0.0028)	
Company FE	Yes	Yes	Yes	No[1]
Year FE	Yes	Yes	Yes	No[1]
Observations	8,972	8,971	8,971	8,309
R^2	0.29410	0.29769	0.29785	0.00037
Adjusted R^2	0.09170	0.09591	0.09546	-0.00023

Clustered (Industry) standard-errors in parentheses

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: [1]. In two-stage DID, the fixed effects are included in the first stage model but not the second stage. Only the second stage's outputs are presented in the table. [2]. All units scatter across 62 differnt industries. The dependent variable in all regressions is the percentage of board seats offered to women. In the table, Employees means logarithm transformed yearly average number of employees. Sales is logarithm transformed yearly revenues. COVID-19 Award is logarithm transformed yearly financial assistance received from multiple COVID-19 funding schemes. Number of directors is the average number of directors. A series of Post variables are dummies, representing wthether company$_i$ is bounded by California's gender quota in a certain year k or a period t. Specifically, k means $k - th$ year leading or lagging the implementation of the quota, and the values of k range from -3 to 3. t stands for certain periods. $t = 0$ is the per-treatment period while $t = 1$ is the post-treatment period. For base DID and static DID, excluded category is Post$_{t=0}$. For event study DID and two-stage DID, excluded category is Post$_{k=-1}$. An estimation includes company fixed effect and year fixed effect where noted with "Yes".

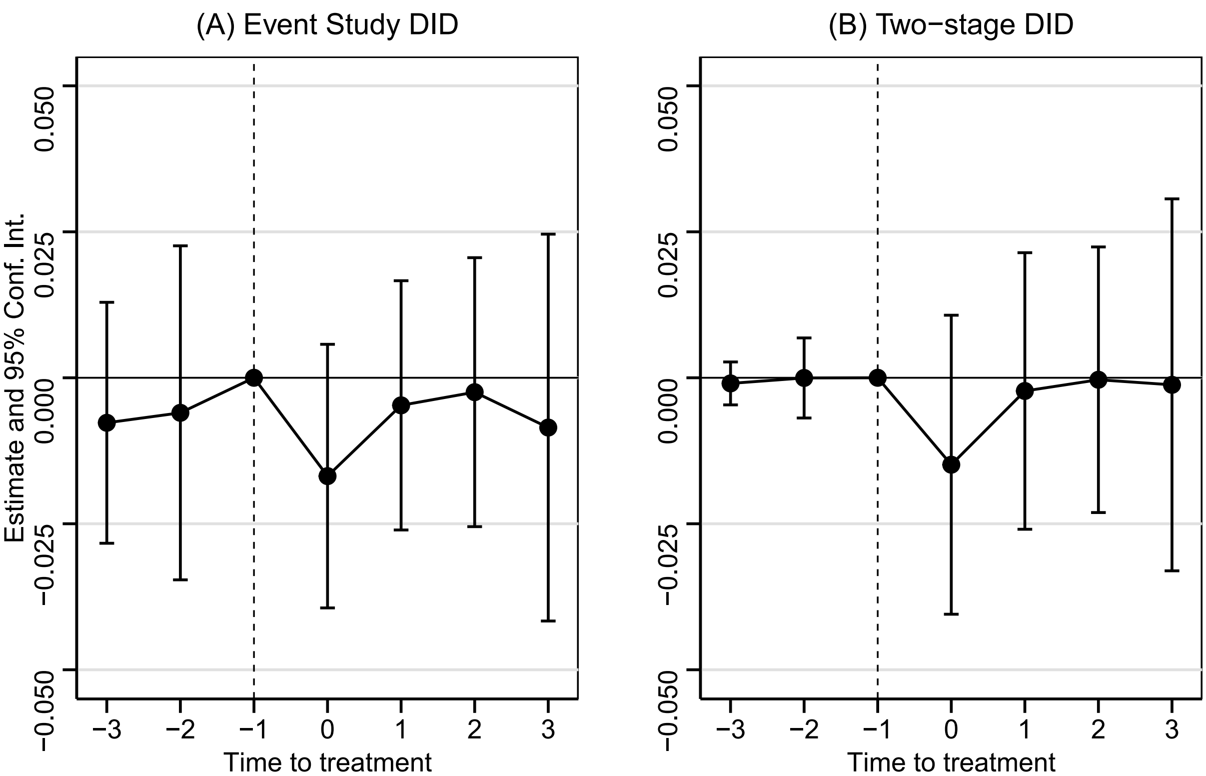

Figure 6: *Disaggregated Effects on Corporate Crime Tendencies (I).*

Notes: Both graph (A) and (B) display how the difference evolves in the number of companies invovled in illegal practises (crime index) between treated and untreated units, while (A) uses outputs from event study DID and (B) from two-stage DID. Each point refers to the difference in the corresponding year. Each error bars shows the 95% confident interval of the matching point estimate. X-axis shows the relative timing of the event initiation. 0 is the year of initiation (i.e. 2018), -1 is the year before 2018 (i.e. 2017), 1 is the year after 2018 (i.e. 2019), and so on. The difference in the year 2017 is the baseline for comprision.

Heterogeneity Analysis on Subgroups (II)

As I demonstrated in Section 5.1 that the female index does not develop evenly across the two sub-treatment groups, a similar analysis of heterogeneity on the crime index is carried out in the same setting. Figure 6 shows that mandatory gender quota does not have an obvious impact on corporate compliance. However, Figure 7 suggests that not both subgroups are consistent with the story. Compared to the control group, "pre-fulfill" group does not act differently in terms of corporate compliance post-event. While "not pre-fulfill" group notably decreases its crime index when compared to the same control group. In 2019 and 2020, "not pre-fulfill" group has a significantly lower crime index. In 2021, the year that treated companies generally should have already included more female board members, "not pre-fulfill" group reaches a further lower crime index than that in previous years.

Similar to findings presented in Section 5.1, a gap in crime index is also detected between "pre-fulfill" and "not pre-fulfill" subgroups. In the "not pre-fulfill" group, I observed a significant decrease in the number of companies involved in illegal activities after 2018. On the contrary, I do not find in "pre-fulfill" group a notable decrease in crime index. A possible explanation for this outcome is the limited number of competent women candidates. If a "pre-fulfill" company already exhausted its pool of qualified female candidates before the initiation of the gender quota, then it would have to hire less competent women who may be lax in corporate compliance.

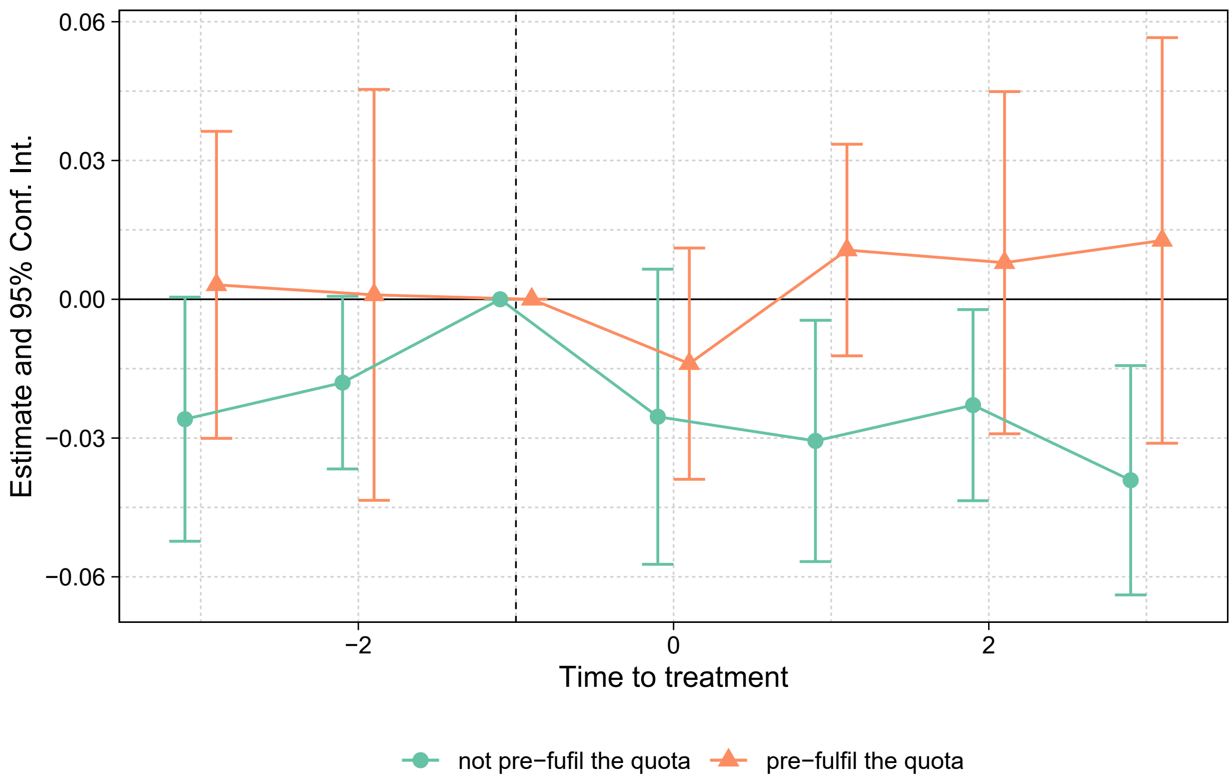

Figure 7: *Disaggregated Effects on Different Subgroups (II).*

Notes: The figure depicts how the differences in crime index evolve across subgroups. Each green point refers to the difference in crime index between "not pre-fuifill" sub-treatment group and control group in corresponding year. Green error bars represent the 95% confidence intervals for respective green points. Each organge triangle points out the difference in crime index between "pre-fuifill" sub-treatment group and control group in corresponding year. Orange error bars display the 95% confidence intervals for respective orange points. X-axis shows the relative timing of the event initiation. 0 is the year of initiation (i.e. 2018), -1 is the year before 2018 (i.e. 2017), 1 is the year after 2018 (i.e. 2019), and so on. The range of x-axis is from -3 to 3.

6 Robustness

Different cluster

As denoted in Equation (1) and Equation (2), I cluster standard errors by the variable of industry. It is because I assume that companies in the same industry may be affected by the same general industry climate or economic environment and then may react similarly. It leads me to assume further that businesses in the same industry have a similar willingness to enhance board diversity or have a similar propensity to commit illegal activities. Based on this assumption, I use the 2-digits SIC industry code[12] as the chosen cluster. To test the

[12]The Standard Industrial Classification (SIC) was a means of classifying industries by a series of multi-digit

robustness, I also use NAICS[13], another industry classification system, to compute clustered standard errors. Besides similarities shared in the same industry, business groups in the same city may also be influenced by the local business environment to some extent. I then use incorporation city to calculate clustered standard errors. The use of different clusters does not cause changes in the level of significance in the specification of event study DID. Consequently, clustered standard error calculated by the 2-digit SIC code is robust. Detailed results of regressions using different clusters are included in Appendix (Table 3)

Different crime source

As discussed in Section 3, I use 8-K filings submitted by sampled firms as a source of their criminal records. Usually, public companies are mandated to publish major litigation information through 8-K filings, or through 10-K and 10-Q filings. It means that 8-K filings issued by a company may not cover all its legal disputes, as some legal proceedings are included in 10-Q or 10-K reports. In addition, companies may suppress reporting some non-critical litigation information because the disclosure of such information is not mandatory.

Based on this situation, I replace 8-K filings used in this study with data downloaded[14] from the Securities Class Action Clearinghouse (SCAC)[15] maintained by Stanford Law School. The clearinghouse keeps a database of 6402 securities class action lawsuits filed in Federal Court. As stated by the clearinghouse, "The complaint of a securities class action generally contains allegations that the company and/or certain of its officers and directors violated one or more of the federal or state securities laws" ("Securities Class Action Clearinghouse: About the SCAC," n.d.). While the clearinghouse does not document all legal cases that public companies are involved, I can still use its data to imitate the number of companies' non-compliance cases. After processing the date, I establish a binary variable indicating whether a company is involved in at least one securities class action in a particular year.

When using criminal records retrieved from 8-k filings, both the event study DID and the two-stage DID capture negative but insignificant point estimates for each year of the post-event period. When using securities class action records to mimic companies' criminal tendencies, event study DID returns positive point estimates in all years post-quota. Presented by

codes. It offers a solution for standardizing industry classification for statistical purposes across agencies. Available on https://www.osha.gov/data/sic-manual

[13]The North American Industry Classification System (NAICS) is a standard industry classification used by Federal statistical agencies. It was adopted to replace SIC. https://www.census.gov/naics/?input=&year=2022

[14]As SCAC does not provide downloading function, I use a python script to crawl data from SCAC. My code is adjusted from a piece of python code shared and written by Kai Chen and his research assistant Shiyu Chen. Original code available on: https://www.kaichen.work/?p=1032

[15]Source: https://securities.stanford.edu/index.html

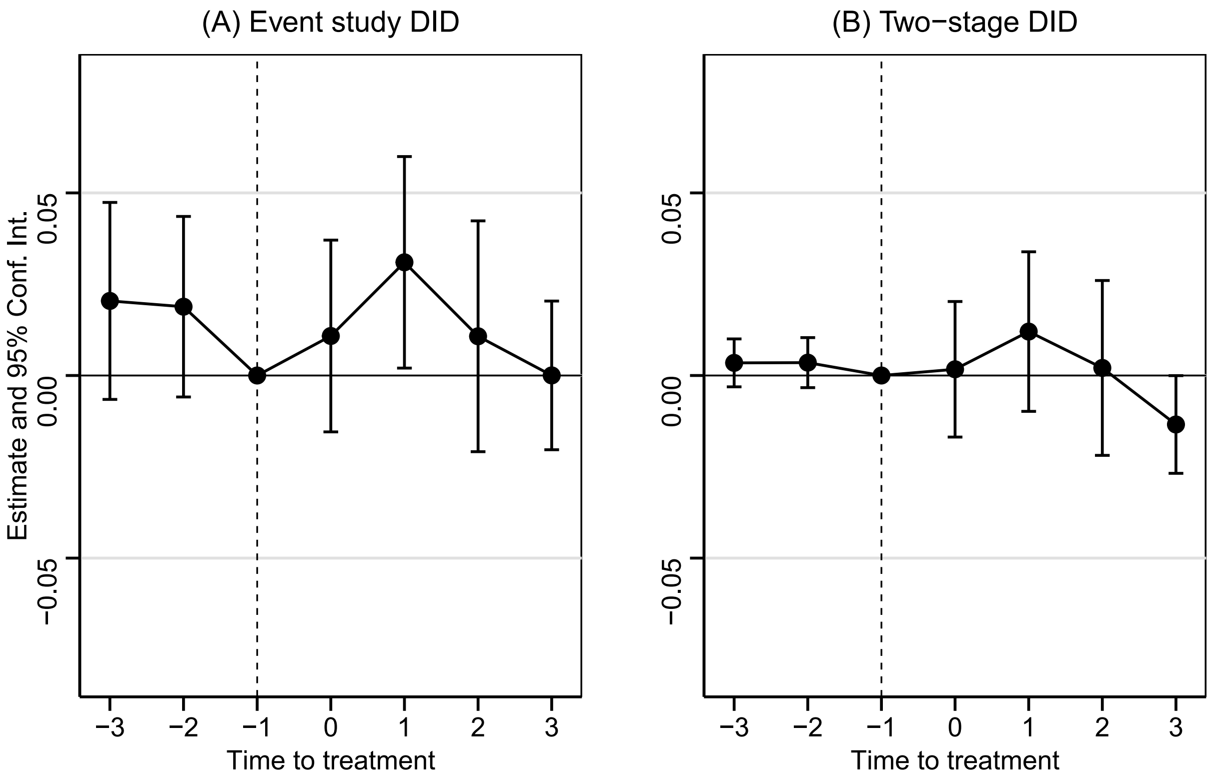

Figure 8: *Disaggregated Effects on Corporate Crime Tendencies (II).*

Notes: Both graph (A) and (B) display how the difference evolves in the number of companies invovled in illegal practises (crime index) between treated and untreated units, while (A) uses outputs from event study DID and (B) from two-stage DID. Each point refers to the difference in the corresponding year. Each error bar shows the 95% confident interval of the matching point estimate. X-axis shows the relative timing of the event initiation. 0 is the year of initiation (i.e. 2018), -1 is the year before 2018 (i.e. 2017), 1 is the year after 2018 (i.e. 2019), and so on. The difference in year 2017 is the baseline for comprision.

Figure 8 graph (A), the positive point estimates for the year 2018, 2020, and 2021 are not statistically significant, while the point estimates for the year 2019 is significantly higher than zero. In other words, considerably more companies engaged in securities class actions in 2019 in California than in control states. In the same context, the two-stage DID gives back different results. As Figure 8 graph (B) denotes, point estimates for years from 2018 to 2020 are more close to zero, especially the point estimate corresponding to the year 2019 is now not statistically significant.

Though the regression results after replacing the data source of criminal records does not overturn the original findings, it denotes that retrieved results may be revised if new data sources are combined to make the criminal records of business groups more comprehensive.

7 Discussion

As proved by this study, California's mandatory gender quota considerably boosts gender parity on corporate boards in CA-based publicly listed companies. In these companies, more and more board seats are offered to women. Previous literature proves that women are less likely to engage in crimes than men.[16] Hence, in the context of the quota, I expect to prove the positive impact of including more female board members on reducing corporate crime. However, this study does not find evidence suggesting a significant decline in corporate delinquent behaviour after more females joined boards in the CA. The possible mechanisms behind this outcome are: (1) female members are still less present in more influential board positions; (2) gender barriers in boardrooms persist; (3) Unbalance supply of competent female candidates.

Female members are still less present in more influential board positions

In 2022, women occupied 31.3% of seats on boards of the largest publicly listed companies in the US.[17] However, women are generally appointed to relatively less important non-executives rather than C-suite positions. Among America's companies from the 2022 Fortune 500 and S&P 500, 16.3% of them have female CFOs, and 8.1% of them have female CEOs.[18] Widening company portfolio to all America's listed firms results in an even lower proportion of female CEOs, at 5%.[19] The presence of women in C-suite positions remains uncommon. Staying on non-key posts without further promotions to more influential roles limits women board members' influence and impact (Whitler and Henretta 2018). It may also hinder women from exerting their influence on inhibiting deleterious corporate behaviour.

Gender barriers in boardrooms persist

Gender-based barriers remain in boardrooms for female board members. Corporate boards as "masculine arena" are full of a "competitive, win-lose culture", which "is likely to pose a barrier to the participation of women" (KONRAD, KRAMER, and ERKUT 2008). It may further discourage women members from influencing and shaping corporate decisions related to compliance.

Unbalanced supply of competent female candidates

As mentioned in Section 5.1, some companies already included female board members before

[16]See Section 2.3
[17]Source: OECD Statistics. https://stats.oecd.org/index.aspx?queryid=54753
[18]Source: Volatility Report 2022 America's Leading Companies published by CRISTKOLDER Associates. https://www.cristkolder.com/volatility-report
[19]Source: Global Gender Diversity 2022 published by ALTRATA. https://altrata.com/reports/global-gender-diversity-2022

the initiation of the gender quota. The supply of competent female candidates is limited and unbalanced across different industries (Greene, Intintoli, and Kahle 2020). Once a company exhausted its pool of qualified female candidates before the initiation of the gender quota, then it would have to hire less competent women who may be slack in corporate compliance.

8 Conclusion

This thesis explores if mandatory gender quota in California affects board diversity in publicly traded companies headquartered in the state and whether including more female board members reduces corporate delinquency. Combining the use of several difference-in-differences methods and the original dataset that covers 1993 companies in six states over seven years, I identify that gender diversity quota has a notable impact on female board representation. However, not in line with some of the previous literature, this study does not find a significant impact of board diversity on corporate compliance. This outcome may be due to the fact that female members are more present in non-key positions in boards rather than in more influential positions. Besides, gender barriers persisting in boardrooms may also hinder women members from exerting their influence on inhibiting deleterious corporate behaviour. In addition, the insufficient supply of capable female candidates may increase the likelihood of companies hiring less capable female directors to meet mandatory quota requirements. These less competitive appointees may be slack in compliance and therefore do not help to reduce corporate deviant behaviour.

This study does have limitations. Although California's gender quota is enacted at a fixed time, the time at which each company actually adds more women to its' board varies, which means the timing that newly added female board members start to influence corporate governance is varying.

As discussed in Section 6, using different data sources to mimic companies' criminal tendencies may return different results. The results obtained in this study may be revised if new data sources are combined to make the criminal records of business groups more comprehensive.

While this study has considered impacts from similar policies in the US that may exist simultaneously to California's gender quota, I may not have exhausted all policies. Also, it cannot be ruled out that some non-similar policies may also have had some impacts on either board diversity or corporate compliance, thus affecting the accuracy of the findings in this article.

Finally, the lack of micro-data, such as survey data and interview data, has hindered the deeper exploration of the relationship between boardroom diversity and corporate compliance. This problem also needs to be addressed by further research.

9 Appendix

9.1 Keywords Used in Crime Dectection

enter(s/ed) into (a) civil settlement(s)

enter(s/ed) into (a) civil litigation(s)

enter(s/ed) into (a) civil agreement(s)

without admitting or denying consent

without admitting or denying (a) order(s)

civil penalty (penalties)

civil money penalty (penalties)

civil monetary penalty (penalties)

disgorgement payment(s)

criminal fine

sec('s) investigation(s)

sec('s) litigation(s)

sec('s) complaint

sec('s) administrative proceeding(s)

cease-and-desist proceeding(s)

cease and desist order(s)

violate(s/ing/ed) ... Act

violate(s/ing/ed) ... law(s)

violation(s)... Act

violation(s) ... law(s)

9.2 Other Figures and Tables

Table 3: *Robustness Tests*

	Gender diversity		Corporate compliance		Corporate compliance[1]	
Clustered by:	naicsh	city	naicsh	city	sic	sic
Model:	(1)	(2)	(3)	(4)	(5)	(6)
$\text{Post}_{i,k=-3}$	-0.0093*	-0.0091*	-0.0077	-0.0077	0.0204	0.0035
	(0.0051)	(0.0051)	(0.0152)	(0.0140)	(0.0138)	(0.0033)
$\text{Post}_{i,k=-2}$	-0.0034	-0.0031	-0.0061	-0.0060	0.0188	0.0035
	(0.0042)	(0.0035)	(0.0162)	(0.0145)	(0.0126)	(0.0035)
$\text{Post}_{i,k=0}$	-0.0050	-0.0050	-0.0158	-0.0168	0.0108	0.0017
	(0.0047)	(0.0038)	(0.0140)	(0.0134)	(0.0134)	(0.0095)
$\text{Post}_{i,k=1}$	0.0200***	0.0201***	-0.0048	-0.0047	0.0310**	0.0120
	(0.0077)	(0.0063)	(0.0134)	(0.0119)	(0.0148)	(0.0112)
$\text{Post}_{i,k=2}$	0.0316***	0.0318***	-0.0029	-0.0025	0.0107	0.0021
	(0.0071)	(0.0071)	(0.0136)	(0.0123)	(0.0161)	(0.0122)
$\text{Post}_{i,k=3}$	0.0639***	0.0643***	-0.0090	-0.0085	2.54×10^{-5}	-0.0134**
	(0.0091)	(0.0106)	(0.0163)	(0.0151)	(0.0104)	(0.0068)
Employees	0.0128	0.0128*	0.0691**	0.0694***	0.0223	
	(0.0086)	(0.0072)	(0.0272)	(0.0239)	(0.0220)	
Sales	0.0044**	0.0043**	-0.0086	-0.0089*	0.0040	
	(0.0020)	(0.0020)	(0.0063)	(0.0051)	(0.0047)	
COVID Award	0.0006	0.0005	-0.0004	-0.0005	-0.0011	
	(0.0010)	(0.0011)	(0.0019)	(0.0012)	(0.0014)	
Number of Directors			0.0057**	0.0058**	0.0030	
			(0.0028)	(0.0025)	(0.0021)	
Company FE	Yes	Yes	Yes	Yes	Yes	No[2]
Year FE	Yes	Yes	Yes	Yes	Yes	No[2]
Clusters	425	274	425	274	62	62
Observations	8,926	8,971	8,926	8,971	8,971	8,309
R^2	0.81381	0.81359	0.29799	0.29785	0.25833	0.00058
Adjusted R^2	0.76025	0.75989	0.09590	0.09546	0.04456	-1.76×10^{-5}

*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Note: [1]. In the regression model, the data source of coporate criminal recors is from the Securities Class Action Clearinghouse. [2]. In two-stage DID, the fixed effects are included in the first stage model but not the second stage. Only the second stage's outputs are presented in the table. naicsh represents industry codes from The North American Industry Classification System (NAICS). "sic" means industry codes from the Standard Industrial Classification. "city" means incorporation city. Employees means logarithm transformed yearly average number of employees. Sales is logarithm transformed yearly revenues. COVID-19 Award is logarithm transformed yearly financial assistance received from multiple COVID-19 funding schemes. Number of Directors is the yearly average number of directors. A series of Post variables are dummies, representing wthether company$_i$ is bounded by California's gender quota in a certain year k or a period t. Specifically, k means $k - th$ year leading or lagging the implementation of the quota, and the values of k range from -3 to 3. t stands for certain periods. $t = 0$ is the per-treatment period while $t = 1$ is the post-treatment period. For base DID and static DID, excluded category is Post$_{t=0}$. For event study DID and two-stage DID, excluded category is Post$_{k=-1}$. An estimation includes company fixed effect and year fixed effect where noted with "Yes".

Reference

Ahern, Kenneth R. 2017. "Information Networks: Evidence from Illegal Insider Trading Tips." *Journal of Financial Economics* 125 (1): 26–47. https://doi.org/10.1016/j.jfineco.2017.03.009.

Akers, Ronald L. 1991. "Self-Control as a General Theory of Crime." *Journal of Quantitative Criminology* 7 (2): 201–11. https://doi.org/10.1007/BF01268629.

Allen, Abigail M., and Aida Sijamic Wahid. 2023. "Regulating Gender Diversity: Evidence from California Senate Bill 826." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4380484.

Baum, Ido, Dalit Gafni, and Ruthy Lazar. 2022. "Gender and Corporate Crime: Do Women on the Board of Directors Reduce Corporate Bad Behavior?" *Michigan Journal of Gender & Law*, no. 29.2: 291. https://doi.org/10.36641/mjgl.29.2.gender.

"Bill Text - SB-826 Corporations: Boards of Directors." 2018. https://leginfo.legislature.ca.gov/faces/billTextClient.xhtml?bill_id=201720180SB826.

"Board Diversity Disclosure Five Things." 2023. https://listingcenter.nasdaq.com/assets/Board%20Diversity%20Disclosure%20Five%20Things.pdf.

Borusyak, Kirill, Xavier Jaravel, and Jann Spiess. 2021. "Revisiting Event Study Designs: Robust and Efficient Estimation." https://doi.org/10.48550/ARXIV.2108.12419.

Campaniello, Nadia, and Evelina Gavrilova. 2018. "Uncovering the Gender Participation Gap in Crime." *European Economic Review*, Gender Differences in the Labor Market, 109 (October): 289–304. https://doi.org/10.1016/j.euroecorev.2018.03.014.

Chaisemartin, Clément de, and Xavier D'Haultfœuille. 2020. "Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects." *American Economic Review* 110 (9): 2964–96. https://doi.org/10.1257/aer.20181169.

"COVID Relief Spending." n.d. https://usaspending.gov/disaster/covid-19.

Daboub, Anthony J., Abdul M. A. Rasheed, Richard L. Priem, and David A. Gray. 1995. "Top Management Team Characteristics and Corporate Illegal Ac." *Academy of Management. The Academy of Management Review* 20 (1): 138. https://www.proquest.com/docview/210968302/abstract/7815A1B839674317PQ/1.

Gardner, John. 2022. "Two-Stage Differences in Differences." https://doi.org/10.48550/ARXIV.2207.05943.

Gertsberg, Marina, Johanna Mollerstrom, and Michaela Pagel. 2021. "Gender Quotas and Support for Women in Board Elections." https://doi.org/10.3386/w28463.

Goodman-Bacon, Andrew. 2021. "Difference-in-Differences with Variation in Treatment Timing." *Journal of Econometrics* 225 (2): 254–77. https://doi.org/10.1016/j.jeconom.20

21.03.014.

Greene, Daniel, Vincent J. Intintoli, and Kathleen M. Kahle. 2020. "Do Board Gender Quotas Affect Firm Value? Evidence from California Senate Bill No. 826." *Journal of Corporate Finance* 60 (February): 101526. https://doi.org/10.1016/j.jcorpfin.2019.101526.

Helwig, Joan. n.d. "More States Promote Gender Diversity on Corporate Boards." https://www.cogencyglobal.com/blog/more-states-promote-gender-diversity-on-corporate-boards.

Johnson, Jonathan L., Catherine M. Daily, and Alan E. Ellstrand. 1996. "Boards of Directors: A Review and Research Agenda." *Journal of Management* 22 (3): 409. https://www.proquest.com/docview/197134929/4BC3CF6DAE834D87PQ/15.

KONRAD, ALISON M., VICKI KRAMER, and SUMRU ERKUT. 2008. "Critical Mass:" *Organizational Dynamics* 37 (2): 145–64. https://doi.org/10.1016/j.orgdyn.2008.02.005.

Maulidi, Ach. 2022. "Gender Board Diversity and Corporate Fraud: Empirical Evidence from US Companies." *Journal of Financial Crime* 30 (2): 309–31. https://doi.org/10.1108/jfc-02-2022-0038.

McLaughlin, Craig, Stephen Armstrong, Maha W. Moustafa, and Ahmed A. Elamer. 2021. "Audit Committee Diversity and Corporate Scandals: Evidence from the UK." *International Journal of Accounting & Information Management* 29 (5): 734–63. https://doi.org/10.1108/ijaim-01-2021-0024.

Posner, Cydney. 2022. "California Appeals Court Reinstates Injunctions Against California Board Diversity Laws." https://corpgov.law.harvard.edu/2022/12/19/california-appeals-court-reinstates-injunctions-against-california-board-diversity-laws/.

"RCW 23B.08.120." n.d. https://app.leg.wa.gov/RCW/default.aspx?cite=23B.08.120.

"Securities Class Action Clearinghouse: About the SCAC." n.d. https://securities.stanford.edu/about-the-scac.html.

Steffensmeier, Darrell, and Emilie Allan. 1996. "Gender and Crime: Toward a Gendered Theory of Female Offending." *Annual Review of Sociology* 22: 459–87. https://www.jstor.org/stable/2083439.

Sun, Liyang, and Sarah Abraham. 2021. "Estimating Dynamic Treatment Effects in Event Studies with Heterogeneous Treatment Effects." *Journal of Econometrics* 225 (2): 175–99. https://doi.org/10.1016/j.jeconom.2020.09.006.

"The Impact of COVID-19 on Organized Crime." 2020. https://www.unodc.org/documents/data-and-analysis/covid/RB_COVID_organized_crime_july13_web.pdf.

Whitler, Kimberly A., and Deborah A. Henretta. 2018. "Why the Influence of Women on Boards Still Lags." *MIT Sloan Management Review* 59 (3): 79–81. https://www.proquest.com/docview/2023988598/abstract/AE4E6261E7AE4E89PQ/1.

"Will More States Set Board Diversity Mandates?" 2020. https://www.lexisnexis.com/com munity/insights/legal/capitol-journal/b/state-net/posts/will-more-states-set-board-diversity-mandates.

Williams, Robert J., J. Douglas Barrett, and Mary Brabston. 2000. “Managers’ Business School Education and Military Service: Possible Links to Corporate Criminal Activity.” *Human Relations* 53 (5): 691–712. https://www.proquest.com/docview/231509781/abstract/44297A6CF74C49B9PQ/1.

Williams, Robert J., Paul A. Fadil, and Robert W. Armstrong. 2005. “Top Management Team Tenure and Corporate Illegal Activity: The Moderating Influence of Board Size.” *Journal of Managerial Issues: JMI* 17 (4): 479–93. https://www.proquest.com/docview/194165290/abstract/E608C5E5731D438EPQ/1.

“Women on Boards.” n.d. https://www.sos.ca.gov/business-programs/women-boards.