Major in Managerial and Financial Economics

Research Paper

Academic Year 2021 - 2022

Do board gender quotas affect how people perceive firms? A study of the California board gender quota law with Twitter sentiment data

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☒ **Rapport ouvert au public** – *Public report* ☐ **Rapport confidentiel** - *Confidential report*

Abstract

The first compulsory board gender diversity quota law in the United States was approved in 2018 in California. In this study, we aim to analyse how public perception has been influenced by the application of this gender quota law, using Twitter Sentiment Score of public companies affected by it. Specifically, the whole Twitter history between 2016-2021 of approximately 200 firms has been scrapped and the daily, monthly and yearly sentiment score has been computed. Moreover, the gender of the account associated with the tweet has been analysed in order to test differences between male and female sentiment. The results show that there is a positive effect of the increase in share of women in the board on the percentage of positive tweets. Moreover, the effects of the pool of tweets of women and men are opposite, positive for women and negative for men. Finally, the effect of the California gender quota law on Twitter sentiment has been studied. Those companies with a lower share of women(do not comply with the law after it was passed) experienced a higher increase in share of positive tweets in the post law period compared with the companies that were already complying with the law.

Keywords: Twitter sentiment score (TSS), Social Media Data, board of directors, gender diversity, female directors, gender quotas.

Acknowledgements

Having the opportunity to study a MiM with a major in Finance and Economics in HEC Paris has been a great honour and it has allowed me to grow both intellectually and emotionally.

I would like to thank HEC, the program coordinator, and the program managers – Ai Ting Goh and Olivier Klein – for their dedication to us during this pandemic time. I would like to thank all the community of professors which prove that we are in the best school.

HEC teaches traditional subjects like Economics, Strategy and Finance but it is also a place where new topics and ideas can be discussed in a stimulating environment. The 5 week Climate and Business Certificate has given me the opportunity to understand and reflect about topics that were not in my vital compass before but that I will be thinking about when making future career decisions. I will never forget this immersive and disruptive experience offered and the human connection I made during those 5 weeks.

I would like to thank my supervisor, Jean-Noël Barrot, who guided me to better understand the research topic and how to use an innovative kind of data like social media data to bring a new perspective to gender diversity issues.

I would also like to thank Floris Van Dijk for his help and long discussions about how to deal with the econometrics work of this project. I met Floris in my M1 and since then we have been collaborating in a handful of projects by mixing my coding skills with his economics research mind, achieving great success.

I believe that the fact that HEC brings together people from very diverse backgrounds and nationalities is an invaluable asset. The opportunity to meet and collaborate with people with very different profiles than mine has allowed me to grow both professionally and personally and understand in a deeper way what I want to do in the future.

All of that would not have been possible without the comprehension of my girlfriend Paula, my parents and family and friends, who have been supporting me from Barcelona throughout these 3 years.

Thanks a lot again to everybody which helped me in making this academic and personal journey a success.

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Introduction

Gender Quotas Research

There has been an increasing pressure on companies by society and business actors to increase diversity in the workplace, including gender, race and religious diversity. While most actors agree that this trend is positive, there is a high discrepancy in how this diversity should be achieved and if imposing mandatory quotas is the best solution to foster the consolidation of diversity in the workplace.

The focus of this kind of research is to study gender diversity issues and board quota legislation. Gender diversity and the implementation of mandated board quotas has been studied using legislation and sets of companies from many countries and study periods.

Most of the latest research focuses on understanding what is the economic impact of gender quotas such whether gender diversity increases firm value, what are the immediate effects on shareholder value of imposing gender quotas on the board of directors or what is the effect of sudden changes in the pool of available female directors on the effectiveness of board gender quotas to name some concrete examples.

These research topics are very focused on what companies should do when deciding whether or not to pursue gender diversity policies to increase long term value and whether or not investors should consider gender diversity as a requirement for their investment strategy.

Twitter Sentiment Analysis Research

However, the research objective of this study is to analyse how people perceive the application of gender diversity policies inside companies and whether or not companies with a strong percentage of women in the board of directors are discerned as more positive by customers and general citizens.

By using Twitter data and performing Sentiment Analysis, the perception that people have on companies over time can be analysed to understand if the fact that some companies are applying strong gender policies whereas other companies continue with business as usual policies has an effect on the positive sentiment on those companies quantified on Twitter.

Twitter data and Sentiment Analysis has been used in research papers both applied to company level data and to macroeconomic and socio-political data. In the first field, the main application of Twitter sentiment data has been to understand the perception that people have on some company decisions, like CEO appointments or some external shocks such as stock crashes or business scandals, and to assess how past Twitter sentiment can predict future stock returns.

In the second field, the core of the research has zoomed into understanding the correlation between Twitter sentiment score and several socio-economic indicators such as GDP (Gross Domestic Product) per capita, political stability, covid lockdowns, economic development, poverty and share of unemployment.

Contributions of this master thesis

The combination of board gender quotas analysis and company Twitter Sentiment Score evolution over time is an innovative research question. In addition, understanding what variables affect the Twitter Sentiment Score evolution can be explored using different kinds of exogenous shocks like the board gender quotas laws from different countries or the closing of a factory. In this thesis, the California board gender quota law has been used.

Using company level data of the Twitter sentiment score over a long period of time and the percentage of women in the board of directors before and after the passing of the board gender quota law several questions can be answered:

- Firstly, which are the effects of the proactive application of gender equality policies on the perception that customers and people have of companies?

- Secondly, are those companies that are forced to increase the percentage of women in director positions because of the law negatively impacted on their Twitter sentiment score by customers and people in general?

- Finally, is there a difference between how men and women perceive companies on Twitter and whether women care more about the share of women on the board than men when analysing the perception of a company on Twitter?

In this paper, the objective is to answer these questions by assessing how the first corporate gender board quota passed in the US has affected the appointment of new directors to such boards, using it as an exogenous shock that allows to divide the pool of Californian companies into 2 groups.

Overall, this paper makes two main contributions, the first contribution of this paper is to the gender quota literature. This study is the first aiming to connect the observed increase in female share in boards with the Twitter positivity rate while differentiating between those companies that already comply with law versus those that must adjust their board structure in order to obey the law and avoid the fines and public opinion problem. The second contribution of this paper is a methodological one. Specifically, instead of relying on survey-based techniques or experimental data, it directly scraps Twitter data from individual users to measure changes in sentiment towards companies. In a sense, this thesis is a “proof of concept” that this publicly-available data can be used in future research.

Paper Structure

The paper structure is detailed below. Section 2 explains the theoretical framework detailing the context and details of the California gender quota law and examples of board gender quotas in other geographies. Moreover, it presents the literature review and some conclusions on the effects of board gender quotas laws while introducing the research issue and the hypothesis. Section 3 describes the data, explains how the final dataset has been obtained and describes the empirical methodology with its robustness and pitfalls. Section 4 analyses and discusses the results. Section 5 concludes.

Theoretical Framework

Gender Quotas Policy Background

California's Senate Bill No. 826 is the first law in the United States that imposes a gender quota on corporate boards to public companies headquartered in a specific State (Senate Bill No. 826, 2018). The law was approved on the 30th of September, 2018, by California's governor, and mandated public companies to have at least 1 female director on the board by the end of 2019 and by the end of 2021 this required minimum would increase to 2 female directors for those companies with 5 directors on the boards or to 3 female directors for those companies with 6 or more directors on the boards. Those companies that by the end of 2021 have 4 or less directors would only require to have 1 female director.

The mandated board quota law has some associated penalties for non-compliance. Every year, companies will go through a compliance assessment to certify that they are following the requirements, otherwise the companies will be fined. For the first violation, a monetary fine of 100k $ has been set and 300k $ for the subsequent violations. Moreover, the law requires companies to report their compliance with its requirements by the elaboration of reports to be published on the Internet.

The following table summarises the California board gender quota law requirements and fines:

Table 1. California board gender quota law requirements and fines

<table>
<tr><th>Minimum requirement</th><th>Years to comply</th><th>Penalty</th></tr>
<tr><td>1 woman</td><td>1 (2019)</td><td rowspan="4">$ 100,000 fine for a first violation
$ 300,000 fine for a subsequent violation</td></tr>
<tr><td>3 women at board with 6 directors or more</td><td rowspan="3">3 (2021)</td></tr>
<tr><td>2 women at board with 5 directors</td></tr>
<tr><td>1 woman at board with 4 directors or fewer</td></tr>
</table>

California is a pioneer in the United States in gender diversity in the workplace and as early as in 2013 both the Senate and the House of the State passed a very similar gender quota law, but it did not enter into effect since it was not approved by the Governor, and it only remained as a non-binding Senate Resolution. Other American States such as Illinois, Massachusetts, Colorado and Pennsylvania have passed similar laws in the legislative bodies but all of them were blocked by the respective governors.

On the contrary, in Europe, some countries, such as France, Italy, Belgium, Spain, Iceland, the Netherlands and Norway, have mandated board quotas for women (Winters & Jacobs-Sharma, 2016). Norway was the first country in the world to impose a binding board gender quota in the world. The law was enacted in 2003 and it ordered a 40% share of women on the boards of public companies.

Furthermore, on the 7th of June, 2022, the European Commission passed a bill[1] with EU member States to increase the gender diversity of corporate boards. The bill had been blocked by the Council for 10 years and it imposes that at least 40% of non-executive director posts or 33% of all director posts are held by the under-represented sex. SMEs (Small and Medium Enterprises) with fewer than 250 employees have been excluded and dissuasive penalties have been included but have not yet been set.

Across the United States, women correspond to around[2] 50% of the educated workforce but only 16% of the board seats in companies at the Russell 3000 index are held by women and 21% of these firms do not have any women on the board. Even if the number of female directors on boards is low, there has been an increasing trend among investors to push for having more diverse board composition since more diverse companies create more value in the long run.

For instance, BlackRock's CEO, Larry Fink, in his 2018 annual letter to CEOs, highlighted the importance of having "boards with a diverse mix of genders, ethnicities, career experiences, and ways of thinking have, as a result, a more diverse and aware mindset. They are less likely to succumb to groupthink or miss new threats to a company's business model. And they are better able to identify opportunities that promote long-term growth."

Existing literature on gender quotas

There are mixed views in the literature of what is the real effect of imposing board quotas to increase diversity in companies. Some researchers argue that board quotas are necessary since increasing diversity in leadership positions ends up affecting diversity in the whole organisation whereas others defend that imposing board quotas is not effective since even if quotas are met, either the same women end up in many different boards or inexperienced women end up holding those seats, leading to less potential value creation for that organisation.

For instance, (Sabatier, 2015) studied the French CAC 40 listed companies' economic performance in the period 2008-2012 concluding that gender diversity in the board reduced company inefficiencies allowing firms to get closer to optimal performance with the endogeneity of board gender diversity being controlled. Moreover, the study noted that endogenous firms' attributes such as gender promotion strategies are completely related to gender diversity on the board.

Focusing on the Senate Bill No. 826 (Hwang et al., 2018) found that the passing of the law resulted in a decrease of 1.4% in company value for firms headquartered in California compared to firms in the rest of the United States. They also found that, the higher the number of female directors the company needed to add to comply with the law, the higher that decline was. However, this decrease in shareholder value was not observed in those

[1] https://www.europarl.europa.eu/news/en/press-room/20220603IPR32195/women-on-boards-deal-to-boost-gender-balance-in-companies

[2] Current Population Survey (CPS) 2019, Bureau of Labor Statistics

companies that were already complying with the law. Similar results were observed by (Greene et al., 2020) using also the California Senate Bill as an exogenous shock. In their analysis, the passing of the law resulted in a decrease of 1.4% in company value.

The fact that those American companies headquartered in California that needed to increase the number of women by law had a decrease in value compared with their American counterparts contrasts with the 2012 Credit Suisse report (Credit Suisse, 2012) that found that "large-cap companies with at least one woman on the board have outperformed their peer group with no women on the-board by 26% over the last six years".

For instance, (Ahern & Dittmar, 2012) and (Matsa & Miller, 2013) use the impact of the passing of a board women quota law as an exogenous shock to investigate the impact of imposing gender quotas on firm value.

In the Norwegian case, several studies have highlighted that there was a shareholder value destruction after the passing of the law. However, according to (Eckbo et al., 2022) the announcement of the Norwegian quota had nothing to do with the observed value destruction in the country companies during that period. Moreover, they claim that the total number of potential female directors was substantial enough to accommodate the rise in demand provoked by the implementation of the gender quota.

Another topic in the literature is whether or not the size and experience of the female director pool is enough to impose gender quotas. (Hwang et al., 2018) argue that the increase in number of women in the boards in California headquartered companies is driven by women that were not directors before and very few appointments come from women in the existing director pool. Hence, the overall supply of female directors was increased as a result of the passing of the law. However, according to (Hwang et al., 2018) those women appointed as board members as a result of the passing of the gender equality quota for boards have less board responsibilities compared to non-California companies. This effect is not caused by those female directors being less experienced than male directors.

Some papers have put the focus on some issues after the introduction of the board women quota in Norway in 2003. At the time the board gender quota was introduced, there were fewer women with the necessary experience than comparable male directors. This fact led to a reduced supply pool of female directors available and many experienced female directors ended up being part of many boards at the same time as detailed by (Teigen, 2015) and (Seierstad & Opsahl, 2010). Contrary to what occurred in that case, this was not completely observed after the introduction of the California board gender quota law.

The issue here is that if the supply of female directors with the needed skills and experience required by corporate boards is lower than the demand, there will be search frictions for finding the right matches for each corporate board and the benefits in value creation of increasing gender diversity will be offset by the costs of finding the right female directors. Following this logic, as (Hwang et al., 2018) have pointed out, the introduction of board gender quotas would have a negative effect on company value at least in the short run. As stated before, in the long run, the effect on company value of gender diversity in the board is ultimately positive as the Credit Suisse report states.

This point of view is supported by (Gertsberg et al., 2021), whose study identified that dysfunctional board dynamics are responsible for the Californian companies value decrease that occurred after the passing of the law contrary to the mainstream notion that it was the lack of supply of skilled women director that caused this value decrease. Moreover, their study detected a higher shareholder support for female nominees compared to male nominees both in the pre and post quota period.

(Hwang et al., 2018) observed that the increase in the number of women in companies headquartered in California happens by replacing male directors that were retiring with women thus the board size was very constant in the whole period of study.

Existing literature using Twitter data

The research using Twitter Sentiment Analysis can be divided into 2 main blocks:

- Understanding how a company is perceived over time on Twitter and the effect of certain shocks
- Using Twitter sentiment score to find correlations with some macroeconomic and socio-political variables

On the first block, (Leitch & Sherif, 2017) have studied the relationship between Twitter sentiment score and corporate governance perspectives. Their paper uses the Twitter sentiment score to predict company share returns, finding a negative statistically significant correlation between Twitter sentiment score and CEO succession announcement and stock returns.

Furthermore, (Bollen et al., 2011) have investigated the relationship between indicators of collective mood states derived from general Twitter feeds and the value of the Dow Jones Industrial Average (DJIA) over time. They use advanced text Sentiment Analysis techniques to detect if the tweet was positive or negative but also measuring the mood of the tweet on 6 dimensions (Calm, Alert, Sure, Vital, Kind, and Happy).

Regarding the second block, (Indaco, 2020) has estimated that the total volume of tweets can explain 78% of GDP at a country level and has found that tweets can explain 52% of the variation of GDP across cities in the US by using Twitter data combined with common night-lights proxy.

Twitter data has also been used as a proxy to estimate public opinion mood changes during Covid-19 period. Both (Wang et al., 2020) and (Barrot, 2021) have found a higher decrease in Twitter positivity sentiment in those regions more affected by the Covid-19 health crisis and concomitant restrictions such as severe non generalised lockdowns.

The most advanced research on Twitter data also uses topic modelling techniques that allows a better understanding of the main keywords of each tweet and group together similar tweets to come up with the most debated topics for a period and specific keywords in Twitter.

Hypotheses

The signing of the California board gender quota at the end of September 2018 by the Governor of California was a rather unexpected event since a very similar piece of legislation was not approved 5 years before and he did not provide any guidance on what were his views on the issue.

As detailed in the policy background section, the female board quota law requires companies to adjust their board composition and governance structure rapidly since by the end of 2019 at least 1 director had to be female and between 1, 2 or 3 directors by the end of 2021 depending on the size of the board.

It has been observed that 29 companies (**Supplementary Table 8**) were already complying with the law (2021 requirements) before the passing of it in 2018 since those companies might have a more proactive attitude in applying strong gender policies (Control Group). On the other hand, the bulk of the companies needed to add at least 1 director or more in order to comply with the law, signalling a passive role in developing internal programmes to foster gender equality in general and in the board in particular (Treated Group).

Due to the introduction of the gender quota law in California and even if the supply of capable female directors might have been lower than the demand after the shock, it can be assumed that companies wanted to comply with the law and have increased their expertise at finding better female directors to occupy board positions. Hence, the first set of hypotheses is as follows:

Hypothesis 1a. *The proportion of women on boards in firms headquartered in California has increased from 2016 to 2022.*

Hypothesis 1b. *Some companies are more affected by the passing of the law since they have a shortfall of female directors and need to hire female directors (Treated group).*

Hypothesis 1c. *The increase in the share of women in the board is higher for the Treated group since they need to adjust board composition to comply with the law.*

Hypothesis 1d. *The increase in the share of women in the board is higher for firms headquartered in California that did not comply with the law initially (Treated group) compared to firms headquartered in other states (NY and Washington).*

By introducing the Twitter sentiment data of the companies, the objective is to explore the relationship between the Twitter sentiment rate over time and the percentage of women on the board. Furthermore, due to the level of granularity of the data, the different effect on the Twitter sentiment rate between female and male Twitter accounts can be computed. Hence, it is interesting to understand what is the effect of an increase in share of women in the board in the evolution of the Twitter sentiment score observed and whether there is a different effect by gender division.

With the previous paragraph explanation and the research issue in mind, a new set of hypothesis can be presented:

Hypothesis 2a. *An increase in the share of women in the board has a positive effect on the sentiment towards the company, i.e. those companies that have more women in the main governing body are better managed and customers should perceive those companies more positively.*

Hypothesis 2b. *The Twitter sentiment rate should have a stronger positive correlation with the share of women in the board when that sentiment rate comes from tweets made by women, i.e. women should value more the fact that the company has a strong gender diversity governance and hence the Twitter sentiment rate should be higher than men*

Finally, considering the implications of the passing of the California board gender quota law and the share of women on the board on how customers and general people perceive the companies in Twitter, it is interesting to explore if those firms that had to increase the share of women because they had a shortfall of women directors to comply with the law (Treated group), get a positive increase in the sentiment or not.

Conversely, the possibility that people perceive better those companies that do not have to increase the share of women because they already comply with the law will be looked into. In addition, the effects of gender can be investigated to assess if the change in Twitter sentiment rate is more pronounced for females than for male.

The following hypothesis are used to evaluate whether the change in sentiment comes from a law or from the company's gender diversity governance affects the magnitude of this positive effect

Hypothesis 3a. *The Twitter sentiment rate of the companies in the Treated group (those companies that have to increase the percentage of women in their boards) has increased more than those that already had a percentage of women in the board in accordance with the gender quota law. Customers and people might appreciate more those companies that promote internally strong gender policies in the company and in the board structure compared to those companies that are forced to do so by legislation but do not apply those practices naturally. In other words, those companies in the treated group experience a lower* *increase in the Twitter sentiment rate between pre and post period than the rest of the companies*

Hypothesis 3b. *The Twitter sentiment rate increase is lower for the companies in the treated group and even lower when considering the Twitter sentiment rate of female accounts compared with men and unknown accounts, i.e, women perceive more negatively than men those companies which do not have a proactive gender equality policy in the board of directors.*

In sum, the main hypothesis is that an increase in the share of women has a positive effect on the sentiment towards the company. Beyond this core effect, there could be two additional relevant elements.

- First, that gender has an effect: women like the change more than men.
- Second, whether the change comes from a law or from the company's own mission and values affects the magnitude of this positive effect.

Methodology

Data

The dataset is composed of different data sources. Table 2 presents an overview of the main datapoints and from which data sources they were obtained:

Table 2. Main data and data sources used in the study.

Data	Description	Data source
Twitter Sentiment Data	Sentiment score and percentage of positive tweets of the company main account on a daily, monthly, and yearly timeframe for the period 2016-2021	Webscrapped from Twitter and Neural Language Processing to analyse tweet text
Board Composition	Percentage of women in the board for the period 2016-2021	Director level data on board appointments from BoardEx
California Women on the Board quotas	Number of women that need to be on the board depending on the board size	California Senate Bill 826

Twitter Sentiment Data

How many tweets have been scrapped and analysed?

As shown in Supplementary Table 3, the sample consists of the full history of 126 companies headquartered in California during the whole study period (2016-2021) and some more companies that did not have Twitter activity before 2018 (up to 139). Moreover, 52 companies from outside California, located in Washington or New York States, have been included to perform some regressions with a control group completely unconnected with the shock.

Some other studies that also focus on the California gender quota law include in their samples between 300-500 companies after performing filtering and removing companies not really affected. Nonetheless, for this paper since the dependent variable was Twitter Sentiment Score, there were many companies with no Twitter account, customer service account or very low activity. Mainly, those companies with a market cap above 2B $ have been included into the analysis but also not all of them had a valid Twitter account.

In total, the tweet history in the period 2016-2021 of 139 companies based in California and 52 companies based in New York or Washington States has been scraped with a total of almost 100M tweets (specifically, a total of 99.873.227).

When running the script, the computational power of the computers used allowed for scraping between 25-50 tweets per second. In total, between 1100 and 2200 hours of average computational power have been needed. This was achieved by parallelizing the scripts so that tweets from different companies could be scraped simultaneously.

Why use Twitter data?

Twitter data has many advantages when comparing with other platforms such as Facebook or Reddit:

- The data is easily scrapable using open source libraries that allow to obtain millions of past tweets from a given account or keyword.

- The level of granularity of the data is really high, containing valuable meta-data such as geospatial data, socioeconomic indicators and some retrievable personal data.

- The standard format of communication in Twitter has been a short text between 140-280 characters for more than 10 years. On the contrary, other social media platforms incorporate much more heterogeneous forms of communication like links, images and long texts, which are difficult to scrape and to understand the whole meaning of the conversation.

In addition to that, the standard format of Twitter text data allows to apply NLP (Natural Language Processing) techniques such as Sentiment Analysis, topic modelling combined with data science techniques like geospatial clustering and network analysis that allow to deepen the detail which can be obtained using tweets data.

For instance, for this study, Twitter data is of paramount importance to obtain a proxy of how different people perceive a company over time with different levels of detail such as a split by gender and selected timeframes (day, month, year). Using the raw text data and the metadata, a more detailed overview of the person tweeting and its relevance for the studied variable can be obtained.

Issues when scraping and performing Sentiment Analysis on Twitter data

- The Twitter accounts were collected manually to ensure that the Twitter profile was the main account representing that company and that it has meaningful activity.
- Only those companies that have a valid Twitter account have been included. For instance, if a company Twitter account had no activity whatsoever, that company has not been included.
- Due to its unstructured form, little contextual data, abbreviations, misspellings, and slang usage, Sentiment Analysis on Twitter can be difficult.

Company Board Data

Boardex database offers director level data on board appointments which uses 8-K filings. 8-K filings reports provide detailed tracking of director appointments changes. Boardex provides an extensive set of variables on companies governance and board appointments including several variables on directors such as gender, years on the board, salary, experience, industry expertise, etc..

The percentage of women directors in company boards in California and non-California companies in the periods before and after the passing of the gender quota bill is obtained from Boardex.

Empirical approach

Twitter Scraping and Sentiment Analysis Methodology

In Algorithm 1, an overview of the main steps performed by the algorithm and the inputs and outputs of the pipeline is provided.

Twitter data extraction

In order to obtain the evolution of the perception of each company on Twitter, the whole tweet history of users mentioning the company profiles was needed. This has been done setting up a web scraping script that takes as input the company Twitter profile name and the period from when the tweets need to be obtained.

For the Twitter data extraction, the Python library ***snscrape***[3] has been used. This Python library allows to extract data from social networks by taking as input user profiles, hashtags, or searches and time periods and returning the posts or discovered items associated with that account. For this specific analysis, the snscrape's module ***snstwitter*** has been used to scrape the different datapoints of the tweets each company in the sample was mentioned.

Snscrape was chosen among other libraries that perform a similar scraping on Twitter data because of its robustness in obtaining the whole Twitter history of an account or a search tag. Other libraries explored like ***Tweepy***[4], ***Twint***[5] or ***GetOldTweets3*** did not allow to scrape the quantity of tweets needed to perform this analysis.

For instance, ***Tweepy*** uses the Twitter API to connect with Twitter and has a limit of 5000 tweets. ***Twint*** did not have a tweet scraping limitation, but it was not robust enough and the search query did not yield all the tweets referring to that profile name in the period of study.

[3] https://github.com/JustAnotherArchivist/snscrape
[4] https://github.com/tweepy/tweepy
[5] https://github.com/twintproject/twint

In order to only consider relevant and third party tweets for the sentiment, all tweets made by users mentioning the profile of the company have been included in the sample and those tweets made by the company itself or related profiles have been excluded.

Supplementary Table 2 summarises the different variables scrapped per tweet using ***snscrape***.

Sentiment Analysis Pipeline

Sentiment analysis (or *opinion mining*) is a natural language processing (NLP) technique that allows to assess whether non-structured data like text is positive, negative, or neutral. In this case, Sentiment Analysis is applied to the tweet texts of a company over time to monitor customer sentiment towards that company.

The main reason to perform Sentiment Analysis on tweet data (unstructured data) is to be able to have a proxy of how people perceive that company over time.

Once the Twitter data has been extracted, Sentiment Analysis is performed using the tweet text to assign a score on the tweet, with the probability of being a positive tweet. The score goes from -1 (totally negative) to +1 (totally positive).

There are different algorithms to perform Sentiment Analysis using different techniques depending on the quantity of data that needs to be analysed and the accuracy of the model:

- **Rule-based Sentiment Analysis algorithms**: these algorithms analyse the different words used in the tweet and assign a score to the text by using manual rules of the sentiment of each word. Mainly, this type of algorithm identifies positive and negative words and counts the words of each type that appear on the text. Moreover, the rules incorporate some NLP techniques that codify text data such as Stemming (keeping only the base of the word), Tokenization (dividing words into characters or subwords), Part-of-speech tagging (assign a grammatical category to each word) and other methods.

- **Machine Learning Sentiment Analysis algorithms**: a machine learning algorithm has been trained using humanly labelled tweets in order to learn which combination of words correspond to each sentiment. Once an unseen tweet is fed into the classifier model, it uses the model weights computed during the learning phase to assign a sentiment to the new tweet text.

In the experimentation phase, for computing the Sentiment Analysis of each tweet, 3 algorithms of each type have been tested and used to have a more reliable final sentiment score.

Table 3. Overview of different Sentiment Analysis algorithms.

Algorithm	Description	Method type
TextBlob	Simple rule-based API for sentiment analysis	Rule-Based
Vader	Parsimonious rule-based model for sentiment analysis of social media text.	Rule-Based
Flair	A PyTorch-based framework for NLP tasks such as sequence tagging and classification.	Embedding-based
Twitter-Sentiment[6]	Generative recurrent neural networks (GRU) custom sentiment analysis model trained from scratch using 1.4 million labeled tweets	Embedding-based

The rule-based algorithms used have been the ***TextBlob*** and ***NLTK Vader*** libraries, which yield a polarity score (from -1 to 1) and the sentiment of the text with a very simple code implementation. On top of those, ***Flair*** and ***Twitter-Sentiment***, two embedding-based algorithms (in an Embedding-based algorithm words are converted to a vector space) have been used to compare results. Flair algorithm has been trained with normal text whereas the Twitter Sentiment algorithm has been trained using text in tweet format.

Rule-based algorithms are much easier to implement and are extremely fast but sometimes they can yield poor results with longer sentences (more neutral words appear and the score tends to get normalised in neutral) and when sarcasm or jargon is used. On the other hand, Embedding-based algorithms performance is higher but it takes much longer to compute the sentiment. As a comparison, ***Flair*** takes around 50-100 times longer to compute the sentiment than NLTK or TextBlob but yields an accuracy of around 90% whereas ***NLTK*** or ***TextBlob*** accuracy is around 70%.[7]

In the final implementation to obtain the Twitter text sentiment, only the rule-based algorithms have been included. There have been 2 main reasons for this:

- Firstly, due to the large number of tweets to be scrapped and the time needed to obtain the sentiment for those tweet texts, using embedding-based algorithms would have required to set-up a parallelized computing setting, which requires deep technical data engineering skills.
- Secondly, since in this case the text will be from Twitter posts, the total length cannot be above 280 characters, minimising the problem of reduced performance of long texts when using Rule-based methods. Moreover, those tweets texts with very few words that lack context or use slang have not been included in the final pool of tweets to reduce the possibilities of obtaining not accurate predictions.

[6] https://github.com/shahules786/Twitter-Sentiment

[7] https://towardsdatascience.com/the-best-python-sentiment-analysis-package-1-huge-common-mistake-d6da9ad6cdeb

Using the polarity score obtained averaging both rule-based algorithms implemented, the raw sentiment of each tweet has been computed. Each tweet receives a positive, neutral or negative label. Finally, different time-dependent metrics have been computed to understand the evolution of the perception of each company in Twitter. Those metrics have been computed by grouping all tweets on a daily, monthly and yearly time frame and calculating the average, median and count of those metrics on each timeframe.

The different time-dependent sentiment metrics computed from the raw polarity score are:

- The same polarity score and total number of tweets has been computed on a daily, monthly, and yearly time frame.
- The number and percentage of positive, negative, and neutral tweets has been computed using the same timeframes. A tweet is considered positive when polarity score is above 0, negativity when is below 0 and neutral otherwise.
- The time averaged polarity score has been normalised by using an engagement weight that gives a higher weight to the sentiment of those tweets that have higher likes, replies and retweets.

In addition to obtaining the tweet sentiment and user data provided by Twitter like the device from where the tweet was sent (if it was a smart phone: Iphone, Android, etc), in order to have data on a more granular level, the gender of the person making the tweet has been computed by using an algorithm[8] trained to recognize names and classify them between male or female. The variable *Displayname* has been used to extract the first and last name of the user making that tweet. By inputting the first name to the trained classifier, it is able to predict if that name is a male or female name and a gender label is attributed to that tweet.

Around 50% of tweets have been labelled either as male or female, the rest are kept as unknown. This low efficiency is because most of the users do not use their real name in their Twitter account and hence the algorithm cannot determine a gender when there is not a recognizable first name associated with that account. Nonetheless, the sentiment score of the Unknown category compared to the male category is quite similar and thus it might be considered that the bulk of the unknown category is composed of men profiles and a minimal part of women accounts. In summary, by implementing this step, time-dependent sentiment metrics with a gender label are obtained.

[8] https://pypi.org/project/gender-guesser/

Regressions Analyses

The regressions analyses include the following empirical approach:

First, using DiD, we determine whether the effectiveness of the Californian law was real, meaning that those companies that were not complying with the law when it was passed, increased their share of women in the board significantly.

Second, using panel data, we determine the effects of changes in the share of women on board on the sentiment towards the company. Moreover, whether the sentiment score is affected by the gender of the Twitter user and by the "forced" (by law) or "voluntary" nature of the change in the share of women on the board has been analysed.

Regressions specification

In this paper, we rely on fixed effects panel methods (the appendix contains a lengthier justification for this). An analysis of the evolution in the share of women on the board is conducted to assess if the increase in share of women can be attributed to the gender quota law while considering controls on firm level. The mandatory level of women in the board for 2021 is considered as baseline and the shortfall variable is constructed to determine how many women are needed to be included in the board in a given year in order to comply with the law.

The shortfall variable has been computed by comparing the actual number of women in the board with the required number of women mandated by the board women quota law, which is dependent, as it has been explained in the policy background section, on board size and the year.

Using the shortfall variable for each company in the year 2018, companies can be separated into 2 groups. One group that has the right share of women in the board before the law was passed and they do not need to adjust and another group that needs to incorporate women into the board and hence they need to adjust their board structure.

2018 has been chosen to separate between pre and post period since companies knew about this change by the end of 2018 and it would have been really difficult for them to already start changing board members so suddenly.

Next, the Treated variable can be created by computing if the company has a positive shortfall in year 2018, meaning that they need to increase the number of women, in which case Treated takes as value 1, and it takes the value of 0 when the company has 0 or a negative shortfall, meaning that with the company's current share of women in the board it is already complying with the mandated gender board quotas. In order to capture the effect of the law in the increase of share of women, a differentiation between the years prior to the passing of the law and the years post its passing needs to be defined. The post period variable has been created to account for the difference between the period before the law was passed and the period after, when companies needed to increase the share of women to comply with the law, the years 2019, 2020, 2021 and 2022 are set as post whereas the years 2016, 2017 and 2018 are set as pre.

Regression 1: DiD to Determine the effectiveness of the Californian law

In order to determine how the law affected the relative speed at which the shares of women on the boards increased during the studied time period, we performed a Difference-in-differences (DiD) regression. For this, we rely on the following DiD regression with year dummies for the three years between the law's announcement and the year it came into effect.

$$ShareFemale_{firm,year} = \beta_1 * Treated_{firm} + \sum_{i=2019}^{2021} (\beta_i * 1_{\{year=i\}} * Treated_{firm}) + \alpha_{year} + \varepsilon_{firm}$$

This allows the decomposition of the increase of the shares of women on the board of the treated companies relative to those of the control companies.

Regression 2.1.1a: The effect of changes in the ShareWomenBoard on sentiment

$$ChangeSentiment_{firm} = \alpha + \beta_1 * ChangeShareWomanBoard_{firm} + \varepsilon_{firm}$$

Now, we want to study the effect of a change in the share of women on the board in the change in sentiment. To achieve this, the the ChangeSentiment and ChangeShareWomanBoard are obtained by taking the value for 2021 minus that of 2019

The value of ChangeSentiment is the average across genders, hence, with all the tweets included without differentiating by gender.

This regression will allow to understand what is the correlation between changes in these 2 variables of interest and define if this correlation has a positive or negative trend with all the companies together and without gender differentiation.

To avoid including non-significant companies that have very few observations, those companies that have less than 100 positive tweets in a given year will be excluded.

Regression 2.1.1b: The effect of changes in the WomenShareBoard on sentiment

$$Sentiment_{year,firm} = \beta_1 * ShareWomanBoard_{year,firm} + \alpha_{year} + \alpha_{firm} + \varepsilon_{year,firm}$$

With this regression, the problem of having very few observations when computing the change between 2 year is overcame. Thanks to using panel data in combination with a pooled OLS model and a fixed effects model for company effects alone and company effects and time effects combined.

In this regression, the panel data has observations for each company and for the years 2016, 2017, 2018, 2019, 2020, 2021. The value of ChangeSentiment is the average across genders.

Regression 2.1.2a: The effect of changes in the WomenShareBoard on sentiment with gender effects

$$Sentiment_{year,gender,firm} = \beta_1 * ShareWomanBoard_{year,firm} + \beta_2 * ShareWomanBoard_{year,firm} * Female_{gender} + \beta_3 * ShareWomanBoard_{year,firm} * Male_{gender} + \alpha_{gender} + \alpha_{year} + \alpha_{firm} + \varepsilon_{year,gender,firm}$$

This regression objective is to capture the same effects than the 2.1.1b regression but having them by gender. The baseline regression only captures how the share of women in the board affects the sentiment rate of that company but without controlling by gender

In order to include the effects of gender, the interaction between the share of women in the board and the dummy variable Female and Male respectively have been created.There are 2 dummy variables by gender since it includes 3 categories: the male, female and unknown.

In this regression, the panel data has observations for each company and for the years 2016, 2017, 2018, 2019, 2020, 2021. Moreover, the value is unique per gender (there are 3 genders)

Regression 2.2.1: The effect of changes in WomanShare on changes in sentiment

$$Sentiment_{year,firm} = \beta_1 * ShareWomanBoard_{year,firm} + \alpha_{firm} + \alpha_{year} + \varepsilon_{firm}$$

In this regression, only the tweet data for 2018, 2019, 2020 and 2021 is considered.
The reason why observations prior to 2018 are not included is because the behaviours of the two groups of companies did not differ before the law was announced because the changes in ShareWomanBoard prior to 2018 were not « forced »

Regression 2.2.2: The effect of quota-based vs voluntary increases in WomanShare on changes in sentiment

$$Sentiment_{year,firm} = \beta_1 * ShareWomanBoard_{year,firm} + \beta_2 * Treated_{firm} * ShareWomanBoard_{year,firm} + \alpha_{firm} + \alpha_{year} + \varepsilon_{firm}$$

With this regression the effect of the California board quota law on how companies were perceived in Twitter depending on whether or not they are on the Treated group can be computed. (Values for 2018, 2019, 2020, 2021)

Results and Discussion

Descriptive statistics

For a deeper and customisable analysis of the data used in the study, a web application has been created using ***streamlit*** Python library. This app allows to evaluate the descriptive statistics for each company, including variables such as monthly and annual tweet count, tweet polarity, and percentage of positive-negative-neutral tweets (**Supplementary Figure 1**). Furthermore, these variables can also be explored by gender (**Supplementary Figure 2**).

The application also allows to explore different descriptive variables of the companies, such as number of directors, nationality mix and women directors, by sector and by year.

As shown in **Supplementary Figures 3 and 4**, there is a general tendency of the companies in the treated group to increase the number of women directors during the law period, whereas this increasing tendency is not so apparent in companies from the non-Treated group. These figures show what was the share of women in the board of each company before and after the law and it can be seen that for the Treated group the general trend is to increase since they were forced to do so by the law.

Moreover, by looking at **Suplementary Figure 5 and Suplementary Figure 6**, the correlation matrix calculated with California and Non-California companies it can be seen that both groups have similar correlations in the Twitter sentiment metrics.

With **Supplementary Table 9,** the evolution of the share of women on the board and the different Twitter sentiment analysis metrics can be observed divided between the Treated and Control group. It can be seen that the sentiment increases or gets maintained for the Treated group, which increases the share of women, whereas for the Control group the share of women is stable but the sentiment decreases in the last 2 years.

Effective application of the Californian law

Regression Results 1 shows the results of the DiD regression **(Regression 1)**. In the year of the law's announcement, the treated group had (as is expected) a significantly lower share of women on the board, namely 18.8 percentage points lower. By the time that the law went into effect, this decreased to only 6.2 percentage points.

However, interestingly, we find that the law had a gradual effect on this reduction. Specifically, of the reduced difference of 12.6 percentage points, 44% (5.5 percentage points) took place in the first year, 28% (3.5) in 2020 and the final 28% (3.5) in early 2021. These results suggest that the treated group gradually started to comply with the law, and thus that the law did not have a brutal one-year effect. This in turn shows that when studying the increases in the number of women on the board, this treated group needs to be taken separately as simply excluding one year would probably miss the "forced" nature of the increases.

Regression Results 1. Regression 1: DiD to Determine the effectiveness of the Californian law

OLS Regression Results

Dep. Variable:	Share_Women_directors	R-squared:	0.437
Model:	OLS	Adj. R-squared:	0.432
Method:	Least Squares	F-statistic:	84.23
		Prob (F-statistic):	1.86e-90
		Log-Likelihood:	-2690.9
No. Observations:	768	AIC:	5398.
Df Residuals:	760	BIC:	5435.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	34.3500	1.143	30.042	0.000	32.105	36.595
Treated	-18.8113	1.310	-14.360	0.000	-21.383	-16.240
v_2019	0.0375	1.634	0.023	0.982	-3.170	3.245
v_2020	1.2138	1.643	0.739	0.460	-2.011	4.438
v_2021	1.9625	1.715	1.144	0.253	-1.404	5.329
v_2019_Treated	5.5199	1.871	2.950	0.003	1.846	9.194
v_2020_Treated	8.9819	1.884	4.768	0.000	5.284	12.680
v_2021_Treated	12.5785	1.972	6.377	0.000	8.707	16.451

Omnibus:	14.957	Durbin-Watson:	1.091
Prob(Omnibus):	0.001	Jarque-Bera (JB):	16.942
Skew:	0.269	Prob(JB):	0.000209
Kurtosis:	3.489	Cond. No.	17.9

Finally, to determine whether this is the result of the Californian law or of a nationwide trend, we perform an additional regression, the results of which can be found in the appendix in **Supplementary Table 11**. These show that, when excluding Californian companies, the interaction effects are non-significant, meaning that the treated group did not increase its shares of women on the board more quickly than the control group. In sum, this suggests that the Californian law managed to force Californian companies that did not comply to increase the share of women more strongly than they would have otherwise.

Main regression results

California companies regression 2.1.1a

Regression Results 2 shows the results of the OLS regression (Regression 2.1.1 a). We can see that the results are not significant due to the fact that there are only 90 companies with a level of positive tweets that is significant in one year. Since there is only 1 observation per company, it is really difficult to obtain significant results. This problem can be mitigated by performing OLS models using panel data such as pooled OLS and fixed effects.

Even if the results are not significant, the result coefficients can be useful to understand the overall trend and confirm it with more robust regressions later on. For a firm whose change in share of women in the board between 2019 and 2021 is 0, the change in sentiment over the same period is -1.15 percentage points and for each increase in percentage point in the share of women in the board between 2019 and 2021 is 0.05 percent points. For instance, if one woman is added to a board of 9, this increases the percentage of women by around 10 percentage points and the total change in sentiment by that increase would be of 0.55 percentage points.

Regression Results 2. Regression 2.1.1a: The effect of changes in the WomenShareBoard on sentiment

OLS Regression Results

Dep. Variable:	Change_Sentiment	R-squared:	0.005
Model:	OLS	Adj. R-squared:	-0.006
Method:	Least Squares	F-statistic:	0.4684
		Prob (F-statistic):	0.496
		Log-Likelihood:	-295.01
No. Observations:	90	AIC:	594.0
Df Residuals:	88	BIC:	599.0
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	-1.1594	0.840	-1.380	0.171	-2.829	0.510
Change_Share_Women_Board	0.0558	0.081	0.684	0.496	-0.106	0.218

Omnibus:	5.653	Durbin-Watson:	2.018
Prob(Omnibus):	0.059	Jarque-Bera (JB):	5.321
Skew:	-0.420	Prob(JB):	0.0699
Kurtosis:	3.845	Cond. No.	12.7

Regression 2.1.1b: The effect of changes in the WomenShareBoard on sentiment

Regression Results 3 shows the results of the fixed effects and pooled OLS models compare(Regression 2.1.1 b). In between parentheses, the T-stat is shown. The full results of these regressions can be found in the appendix as **Supplementary Table 11.**

The Pooled OLS and Fixed Effects II regressions yield not significant results whereas the Fixed Effects I is significant.

For each increase in percentage point in the share of women directors, the percentage of positive tweets would increase on average by 0.18 percentage points. For instance, if 1 woman is added to a board of 9, this increases the percentage of women by around 10 percentage points and the total change in sentiment by that increase would be of 1.8 percentage points.

Regression Results 3. 2.1.1b: Comparison Fixed Effects and Pooled OLS

Model Comparison

	Fixed Effects I	Fixed Effects II	Pooled
Dep. Variable	pct_positive_tweets	pct_positive_tweets	pct_positive_tweets
Estimator	PanelOLS	PanelOLS	PooledOLS
No. Observations	776	776	776
Cov. Est.	Unadjusted	Unadjusted	Unadjusted
R-squared	0.0602	0.0048	0.0001
R-Squared (Within)	0.0602	0.0334	0.0073
R-Squared (Between)	-0.0528	-0.0157	-0.0079
R-Squared (Overall)	-0.0310	-0.0024	0.0001
F-statistic	40.488	3.0008	0.1073
P-value (F-stat)	0.0000	0.0837	0.7433
=====================	=====================	=====================	=====================
const	60.496	63.514	64.733
	(81.997)	(71.678)	(68.935)
Share_Women_directors	0.1845	0.0613	0.0115
	(6.3630)	(1.7323)	(0.3276)
=======================	=======================	=======================	=======================
Effects	Entity	Entity	
		Time	

Regression 2.1.2a: The effect of changes in the WomenShareBoard on sentiment with gender effects

Regression Results 4 shows the results of the Fixed Effects and Pooled OLS regressions (Regression 2.1.2b). Both the Fixed Effects and Pooled OLS regressions are significant and they yield the same trend on the twitter sentiment depending on an increase on the share of women, a positive effect on sentiment in the case of tweets made by females and negative effect on sentiment in the case of tweets made by males.

For the sentiment calculated from female tweets, it can be observed that each percentage point increase in the share of women in the board would increase the percentage of positive tweets of female accounts by around 0.11 percentage points. For the sentiment calculated from male tweets, the effect is significant and negative, namely a 0.03 percentage point decrease in the percentage of positive tweets of males accounts for each percentage point increase in the share of women in the board.

Similar results can be observed when substituting the baseline fixed effects approach with a pooled OLS regression. Specifically, these results indicate that a firm that increases the share of women on its board by 10 percentage points would see its sentiment from women increase by 4.6 percent, whereas male sentiment would decrease by 9.17 percent. This corroborates the differences between men and women found in the previous regressions, albeit finding an overall stronger negative reaction on average.

Regression Results 4. 2.1.2a: The effect of changes in the WomenShareBoard on sentiment

Model Comparison

	Fixed Effects	Pooled
Dep. Variable	pct_positive_tweets	pct_positive_tweets
Estimator	PanelOLS	PooledOLS
No. Observations	1677	1677
Cov. Est.	Unadjusted	Unadjusted
R-squared	0.0825	0.0181
R-Squared (Within)	0.0926	0.0510
R-Squared (Between)	-0.0642	-0.0346
R-Squared (Overall)	0.0099	0.0181
F-statistic	46.692	10.257
P-value (F-stat)	0.0000	0.0000
==============================	====================	====================
const	64.780	66.785
	(96.693)	(100.95)
Share_Women_directors	0.0342	-0.0272
	(1.2125)	(-0.9504)
Share_Women_directors_Female	0.1140	0.0731
	(8.5085)	(2.9448)
Share_Women_directors_Male	-0.0368	-0.0645
	(-2.8228)	(-2.6459)
================================	======================	======================
Effects	Entity	
	Time	

Regression 2.2.2: The effect of quota-based vs voluntary increases in WomanShare on changes in sentiment

For this regression, only the pooled OLS model is significant. As it can be seen in **Regression Results 5,** the baseline of percentage of positive tweets for a company that has no women on the board is 67.13 percentage points. For those companies in the control group, the percentage of positive tweets decreases by 0.08 percentage points for each increase in 1 percentage point increase in the share of women in the boards. On the contrary, for those companies in the Treated group, the percentage of positive tweets increases for each percentage point in the share of women on the board. The increase in percentage points in the percentage of positive tweets for the Treated group would be 0.12.

As an example, a company in the Treated group that increases the share of women in the board by 15 percentage points would receive a positive effect on the percentage of positive tweets of 2.4 percentage points, whilst a company in the Control group with the same increase in the share of women in the board would receive a negative effect of 1.7 percentage points. Both effects appear to be significant but the *Share_Women_directors* variable has a p-value of 6.5%.

It is interesting to note these results enter into contradiction with *Hypothesis 3a*, which considered that companies in the Treated group would have a lower level of sentiment rate. However, since the companies in the Treated group have the largest increase in the share of women in the board, people can perceive that they are doing relatively better than those companies that do not need to change since they already comply with the law.

Regression Results 5. Regression 2.2.2: The effect of quota-based vs voluntary increases in WomanShare on changes in sentiment

Model Comparison

	Fixed Effects I	Fixed Effects II	Pooled
Dep. Variable	pct_positive_tweets	pct_positive_tweets	pct_positive_tweets
Estimator	PanelOLS	PanelOLS	PooledOLS
No. Observations	536	536	536
Cov. Est.	Unadjusted	Unadjusted	Unadjusted
R-squared	0.0086	0.0128	0.0322
R-Squared (Within)	0.0086	-0.0004	0.0039
R-Squared (Between)	0.0148	0.0136	0.0227
R-Squared (Overall)	0.0290	0.0277	0.0322
F-statistic	1.7013	2.5205	8.8624
P-value (F-stat)	0.1838	0.0817	0.0002
===============================	=====================	=====================	=====================
const	68.405	67.052	67.138
	(65.247)	(57.166)	(47.568)
Share_Women_directors	-0.1418	-0.1107	-0.0850
	(-1.8420)	(-1.4239)	(-1.8492)
Treated_Share_Women_directors	0.1452	0.1789	0.1288
	(1.7158)	(2.1046)	(3.7862)
=================================	======================	======================	======================
Effects	Entity	Entity	
		Time	

Interpretation of the results

From Regression 1, where the implementation of the board gender quota law in California was checked, it can be seen that the law has been broadly followed and that companies started adjusting to the law early on, with a 5.5 percentage points increase in 2019. Hence, it can be stated that there are 2 differentiated groups in terms of the number of women that need to be incorporated into the boards.

Moreover, to answer one of the research questions posed, by using panel data with a Fixed Effects model, it can be observed that there is a positive correlation between share of women in the board and the percentage of positive tweets, with a 0.18 percentage points increase on average per 1 percentage points of the share of women in the board. This result can be a preliminary indication that those companies with higher numbers of women on the board are better perceived by customers and people.

When gender effects are included, it can be seen in Regression Results 4, there is a different effect in the Twitter positivity rate. This observation was theoritized in hypothesis 2b. The fact that women are more aware of gender issues and would be more prone to change their perception of a company is confirmed by these results.

A surprising result has been found in Regression Results 5. In that regression, the effect of quota-based vs voluntary increases in the share of women in the board on changes in sentiment has been studied. What the results show is contrary to what was theoritized in Hypothesis 3a.

Limitations of the methodology

Number of companies with sufficient size

Some companies have very few associated tweets since their Twitter activity is very minimal and customers and interested people interact with them through other channels. This creates a problem of having a lot of variability in the number of tweets with a mention the company has received in a month. Hence, for some companies the sample of tweets in a month is very large and constant over time whereas for some others there is a lot of variability and very small sample.

For this reason, the companies that had a low tweet number (average <100 tweets per month) have not been included in the final analysis.

A more robust solution to this problem would be not only using the average but other metrics like the median and variance. For instance, by having the distribution of the number of tweets per time period instead of the mean. Those companies that are more volatile can be found more systematically.

Gender of users

As explained before, when predicting the gender of the person making the tweet by using the first name on the user profile some issues arise. Mainly, the fact many users do not have their official name and surnames and hence it is really difficult to pick up their gender. This is potentially an issue since over half the tweets are in this category. However, this limitation can be minimised in the methodology step by performing multi-linear regressions either excluding the unknown category from the total pool of observations or performing separately the multi-linear regression for each gender type.

Company scandals effects on positivity rate

With the Twitter Sentiment Analysis pipeline, the Twitter Sentiment rate on a daily basis has been computed. When there are some days with a very negative polarity rate or a lot of negative tweets this can affect the overall sentiment for that month and lead to biased estimates.
A solution to avoid this would be to exclude those days that can be considered as outliers. A way of doing this would be setting up a median sentiment tweet per day and cape those days that are 3 standard deviations from the median

Loopholes to the gender board quota

Since in this analysis the focus is only on the change in percentage of women in the board it is not possible to distinguish between an increase in the number of women in the board and reduction of men in the board to have less board size to decrease from 7 to 5 so that less women are needed to be included in the board.
For instance, companies could try to take 1 man away and replace with a woman or take out 2 men to decrease board size instead of hiring a woman. It could potentially have some effects but with the current methodology it could not be detected.

Suggestions for future research

Following the points raised and examined throughout this paper, future research could pursue three directions.

First, direct improvements on this study's methodology could verify and extend the presented findings. More advanced econometric techniques, alternative proxies for the studied variables and a larger dataset could be avenues to explore.

Second, it could be interesting to extend the analysis to other countries and alternative legal requirements that have as goal an increased share of women in corporate leadership.

Finally, following this paper's method for measuring changes in the public sentiment towards individual companies could be used for other corporate policies. Beyond the gender composition of the board of directors, changes in ESG strategies could be a fruitful subject to study based on this method.

Conclusion

This master thesis objective has been to examine the impact of the California board gender quota law on how companies are perceived by customers and people in general. Twitter sentiment data has been used to estimate at scale how public companies are perceived in the public area by a very broad public. The companies with a lower share of women in the board experience a negative percentage decrease compared to firms with higher levels of women in the board.

When controlling for gender, it has been observed that women have a positive effect on percentage of positive tweets when increasing the share of women in the board whereas a negative effect has been observed for men.

Moreover, when using the passing of the California gender quota law as an exogenous shock, it has been seen that the Treated group companies have a positive effect on the positivity rate since they increase the share of women in the board more than the Control group. Therefore, those companies that were not complying with the law when it was passed and only started increasing the number of women on the board because they were forced to do it by the law, benefited positively in the percentage of positive tweets ratio.

Overall, this paper sheds new light on the effects of mandatory board gender quotas on companies and how those companies' perception in Twitter is impacted because of differentiated gender policies among companies. Future research can investigate the impact of legal challenges to on board structure on other countries with similar legislation as well using the Twitter Sentiment Analysis methodology to obtain data about other companies and compare with different exogenous shocks.

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Appendix

Content

Supplementary Figures

Supplementary Tables

Code Overview

For implementing the above mentioned methodology, the programming language Python has been used. Mainly, Data Science libraries like ***pandas*** (data wrangling), ***seaborn*** and ***plotly*** (visualisation), ***sklearn*** (regressions), ***TextBlob***, ***NLTK Vader*** and ***Flair*** (Sentiment Analysis), ***snscrape*** (web scraping) and ***streamlit*** (web application).

Moreover, a web application has been created to display the Twitter sentiment rate evolution per company and gender as well as the board composition evolution, presenting several tabs with visualisations, tables and graphs. This application uses the ***streamlit*** Python library as the main framework and is hosted in a Streamlit cloud.

Github Repository

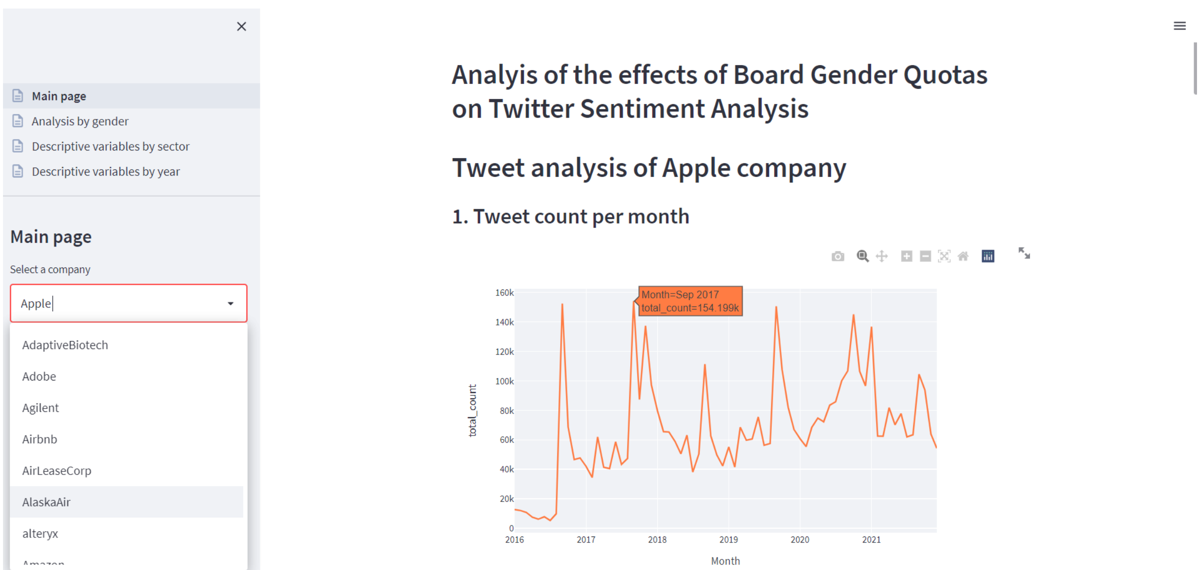
The different scripts in *ipynb* and *py* formats used to perform the different steps of the methodology, analysis, tests and visualisations have been stored publicly in the following Github repositories:

- Analysis: https://github.com/dtm95/master-thesis-twitter-sentiment-analysis-gender-quota-analysis
- Web application: https://github.com/dtm95/master-thesis-twitter-sentiment-analysis-app

Streamlit App

To access to the Web App: [link to access it]

Supplementary Figure 1. Snapshot of the main tab of the App showing analysis of *Apple*.

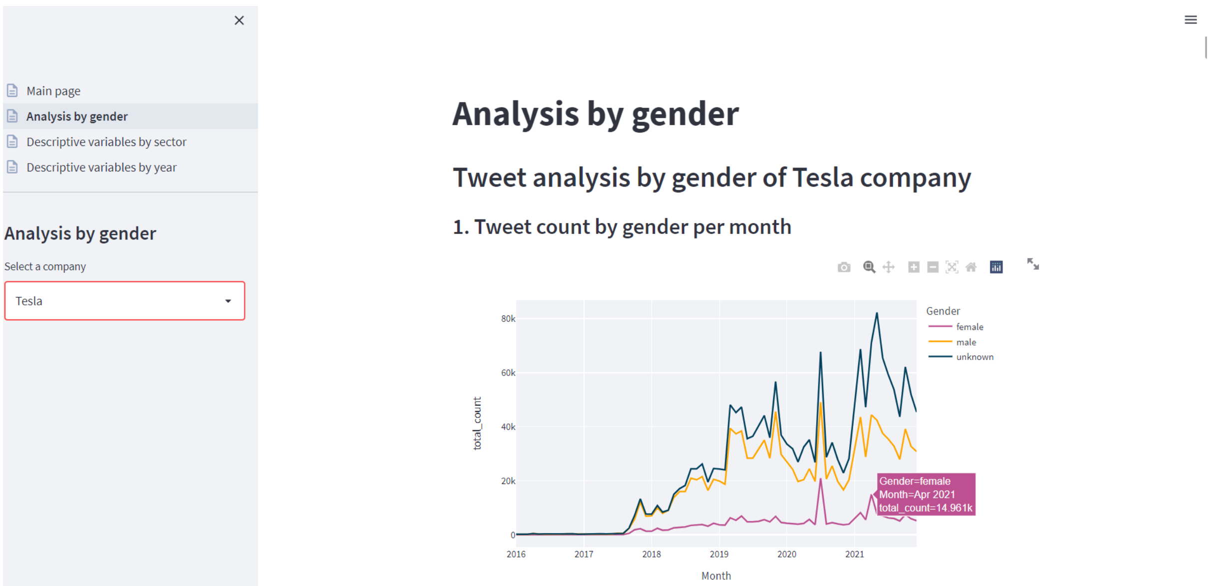


Supplementary Figure 1 shows a snapshot of the main tab of the web application. In this case, the total count of tweets per month mentioning the *Apple* Twitter account is shown. It can be seen how there is a massive increase in tweets for September every year. This spike corresponds to the Apple annual event, where software and hardware releases are announced.

Furthermore, a detailed view of the sentiment on a daily basis is provided to observe some days with a polarity very different from other observations and detect potential outliers visually.

The next tab provides an overview per gender (Supplementary Figure 2). It can be seen how there are very few females tweeting about Tesla since most of the Tweets correspond to the male and unknown category, and it can be seen that the unknown category follows a very similar trend as the male category in terms of polarity and % of positive tweets.

Supplementary Figure 2. Snapshot of the gender analysis tab showing analysis of *Tesla* company.



Code Implementation

As a reference, the optimised code used to compute the Twitter Scraping and Sentiment Analysis Pipeline and a script to load the Twitter sentiment data and board data and perform part of the regression analysis has been included. It can be consulted from the github repository.

Tables and Figures

Twitter Sentiment Analysis Data

Supplementary Table 1. Overview of the algorithm used for Twitter Scraping and Sentiment Analysis

Algorithm 1: Twitter Scrapping and Sentiment Analysis

Data: Companies Twitter Profile List and Tweet Scraping Periods List

Result: Period Timeframe is in days, months and years:

- Polarity rate per company and gender
- Percentage of positive, neutral and negative tweets per company and gender
- Weighted Polarity rate per company and gender

begin

  forall *companies* ***in*** *Companies Twitter Profile List* **do**

    forall *periods* ***in*** *Periods List* **do**

      Twitter Scraping

      - Scrape tweets that mention that account in the text;

      Text Cleaning

      - Exclude tweets made by the company account;
      - Exclude tweets whose language is not English;
      - Process tweet text to get more important words (remove punctuation, hashtags, symbols etc.);

      Sentiment Analysis

      - Predict gender of the user account using first name variable;
      - Apply Sentiment Analysis techniques to tweet text;
        - Rule based Tweet Sentiment Analysis;
          - *Implemented*
        - Machine Learning based Tweet Sentiment Analysis;
          - *Implemented but not used due to computational constraints*
      - Calculate polarity score in each Rule based method;

      Data aggregation

      - Assign sentiment to the tweet depending on the polarity average of that tweet for the 2 rule-based sentiment analysis methods;
      - Calculate percentage of positive, neutral and negative tweets per company and gender;
      - Calculate average polarity rate per company and gender;
      - Calculate a weighted polarity sentiment using engagement metrics such as tweet likes, number of user followers per company and gender;

    end

  end

end

Supplementary Table 2. Variables scrapped per tweet using *snscrape.*

Variable Name	**Variable Description**	***snscrape*'s Tweet Object Attribute**
Datetime	Date the tweet was created	date
Tweet_Id	Unique Id of the tweet	id
Text	Text content of the tweet	content
Username	Name of the user	user.username
Display_Name	Name displayed to other users	user.displayname
User_Description	Profile description displayed to other users	user.description
User_Followers_Count	Twitter accounts following that username	user.followersCount
User_Location	Region that username was created	user.location
Language	Generated with an algorithm. It yields the most probable language of the tweet	lang
Source	Where the tweet was posted from, ex: Iphone, Android	source
Like_Count	Count of likes	likeCount
Reply_Count	Count of replies	replyCount
Retweet_Count	Count of retweet	retweetCount
Quote_Count	Count of users that quoted the tweet and replied	quoteCount

Supplementary Table 3. Evolution number of tweets scraped and number of companies included.

		total_count_tweets				Company
		sum	mean	min	max	nunique
Region	Year					
California	2016	8946780	71006.190476	1	2844006	126
	2017	10669132	83352.593750	1	2830639	128
	2018	12130479	91897.568182	1	2897678	132
	2019	13557903	99690.463235	3	3028544	136
	2020	13970340	101973.284672	1	3617476	137
	2021	11422930	82179.352518	1	2538464	139
non_California	2016	4733494	112702.238095	5	2376117	42
	2017	5353790	116386.739130	2	2522907	46
	2018	5178838	107892.458333	2	2308116	48
	2019	4327915	92083.297872	1	1721106	47
	2020	5045722	98935.725490	1	1971138	51
	2021	4535904	87228.923077	1	1357106	52

Board Data

Supplementary Table 4. Boardex Director Level Data Variables.

Variable Name	Description
BoardName	Name of relevant company/organization.
BoardID	A unique identifier allocated to each company/organization.
TimeRetirement	Time to Retirement for the individual at a selected Annual Report Date assuming a retirement age of 70.
AnnualReportDate	Annual Report Date that that director was on the board
ISIN	An International Securities Identifying Number (ISIN) uniquely identifies a security.
TimeBrd	Time on Board for the individual at a selected Annual Report Date.
Sector	Sector classification of a company under FTSE International classification (In some cases designated by BoardEx).
GenderRatio	The proportion of male directors at the Annual Report Date selected.
NationalityMix	Proportion of Directors from different countries at the Annual Report Date selected.
NumberDirectors	Number of Executive Directors, Supervisory Directors or All of the Directors at the Annual Report Date selected.
NetworkSize	Network size of selected individual (number of overlaps through employment, other activities, and education).

Supplementary Table 5. Variables created ad-hoc for the analysis.

Variable Name	Description
Share_Women_directors	Percentage of women directors in the board
Women_directors	Total number of women directors
Women_directors_law_2019	Women directors required by the law in 2019
Women_directors_law_2021	Women directors required by the law in 2019 which depend on the size of the board
pct_Shortfall_law_2019	Percentage of the share of women above or below the requirements for 2019
pct_Shortfall_law_2021	Percentage of the share of women above or below the requirements for 2021
Shortfall_law_2019	Number of women needed to add to the board to comply with the requirements for 2019
Shortfall_law_2021	Number of women needed to add to the board to comply with the requirements for 2021
Treated	Dummy variable that divides the companies between those that comply with the law (2021 requirements) already in 2018 and those that do not
Post	Dummy variable that divides the year between pre (2016,2017,2018) and post (2019,2020,2021,2022)
Post_Treated	Interaction between Post and Treated

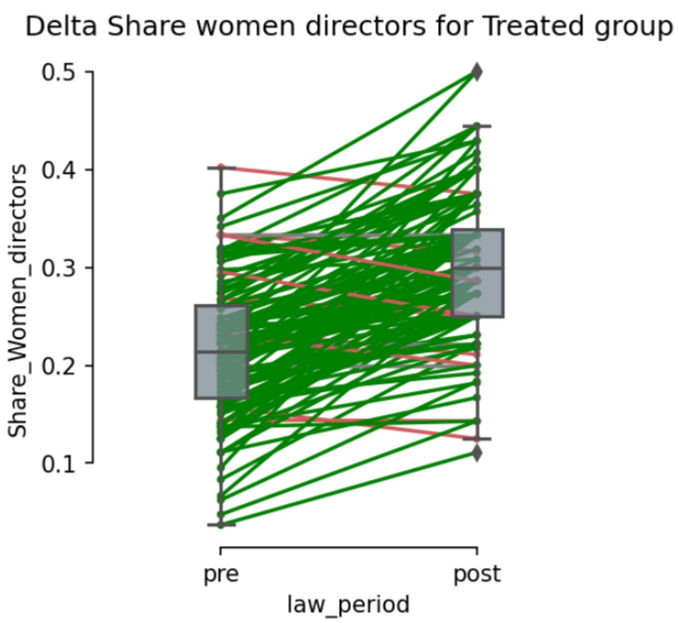
Supplementary Table 6. Evolution of share of women in boards and women directors needed.

	BoardName	Share_Women_directors	NumberDirectors_mean		Women_directors		Shortfall_law_2021	
	count	mean	mean	sum	mean	sum	mean	sum
Year								
2015	175	16.07	8.78	1536.00	1.11	194	1.51	265.00
2016	190	16.62	8.86	1683.99	1.14	216	1.46	277.84
2017	197	18.43	8.87	1747.66	1.29	254	1.30	256.48
2018	210	20.02	8.90	1868.00	1.46	307	1.14	239.98
2019	202	24.25	9.29	1876.00	1.90	383	0.71	142.99
2020	195	28.10	9.29	1812.00	2.29	447	0.38	73.95
2021	161	31.63	9.67	1557.58	2.76	444	-0.05	-8.57
2022	13	34.48	10.00	130.00	3.15	41	-0.54	-7.02

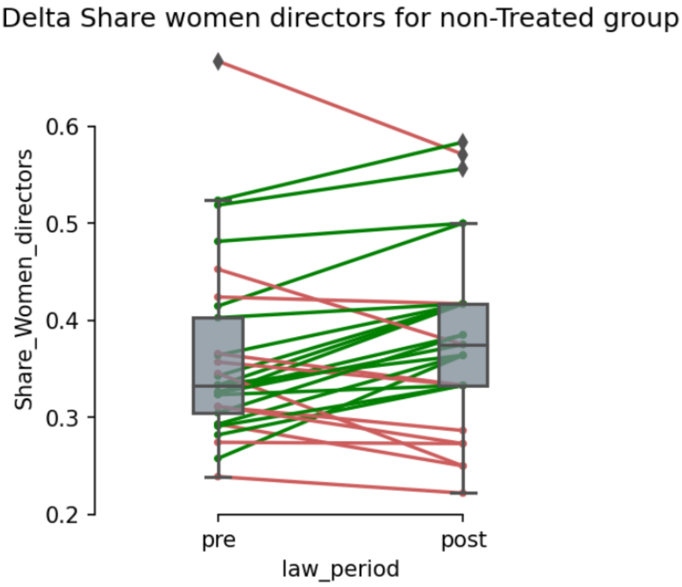
Supplementary Table 7. Evolution of share of women in boards with other diversity and director level variables.

	BoardName	Share_Women_directors	NationalityMix_mean	NetworkSize_mean	TimeBrd_mean	TimeRetirement_mean
	count	mean	mean	mean	mean	mean
Year						
2015	175	16.07	0.13	2356.06	7.26	8.34
2016	190	16.62	0.14	2401.79	7.18	8.44
2017	197	18.43	0.15	2424.02	7.02	8.29
2018	210	20.02	0.15	2509.31	6.78	8.43
2019	202	24.25	0.14	2522.25	6.93	8.14
2020	195	28.10	0.15	2496.96	7.20	7.95
2021	161	31.63	0.14	2582.14	7.61	7.58
2022	13	34.48	0.12	2801.42	8.42	8.04

Supplementary Figure 3. California companies increase in the share of women between pre and post period (Treated group).



Supplementary Figure 4. California companies increase the share of women between pre and post period (Control group).



Supplementary Table 8. Distribution of share of women and shortfall variables between Treated and Control group.

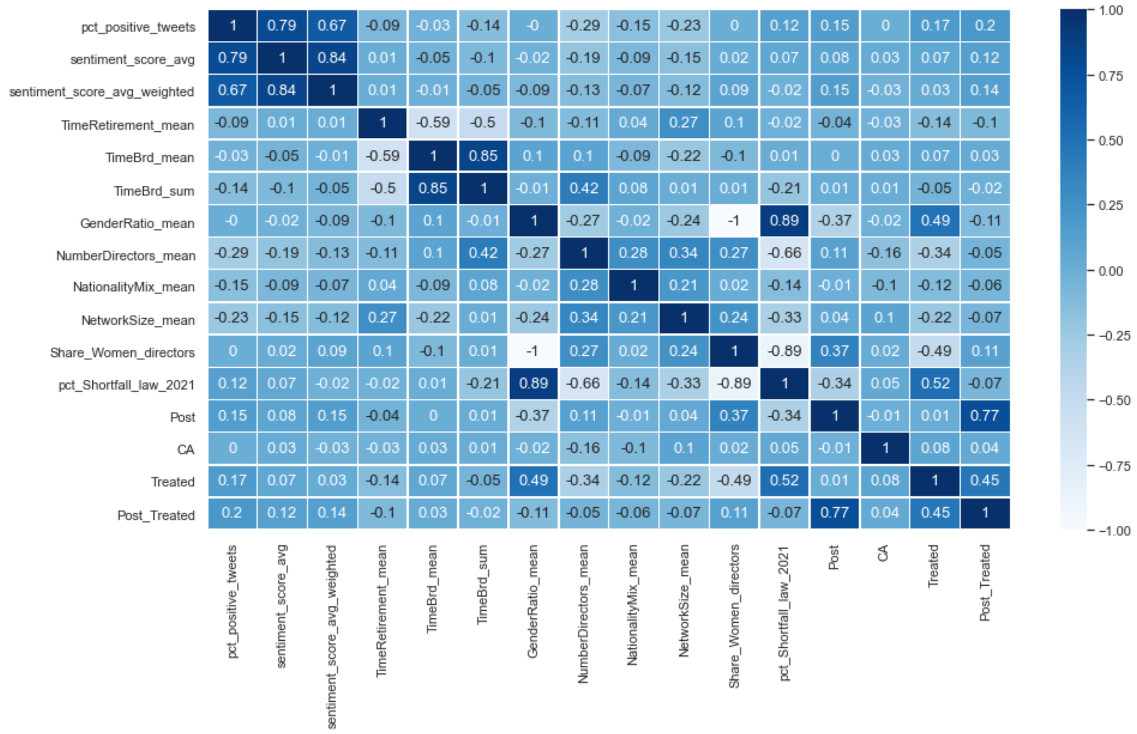
	Treated	count	mean	std	min	25%	50%	75%	max	se	ic 95 lower	ic 95 upper	iqr
Delta_Shortfall	0	29.0	-0.03	0.06	-0.12	-0.08	-0.03	0.01	0.09	0.01	-0.05	-0.00	0.10
	1	132.0	-0.10	0.08	-0.36	-0.14	-0.10	-0.04	0.11	0.01	-0.11	-0.09	0.10
pct_Shortfall_law_2021_post	0	29.0	-0.09	0.08	-0.22	-0.17	-0.09	-0.00	0.11	0.02	-0.12	-0.06	0.17
	1	132.0	0.02	0.09	-0.17	-0.00	0.00	0.10	0.33	0.01	0.01	0.04	0.10
Delta_Share_Women	0	29.0	0.02	0.06	-0.10	-0.02	0.03	0.06	0.11	0.01	-0.00	0.04	0.08
	1	132.0	0.09	0.07	-0.05	0.04	0.08	0.13	0.30	0.01	0.08	0.10	0.09
Share_Women_directors_post	0	29.0	38.08	9.41	22.20	33.30	37.50	41.70	58.35	1.75	34.66	41.51	8.40
	1	132.0	30.37	7.53	11.10	25.00	30.00	33.90	50.00	0.66	29.09	31.66	8.90
Share_Women_directors_pre	0	29.0	36.14	9.36	23.90	30.47	33.30	40.27	66.70	1.74	32.74	39.55	9.80
	1	132.0	21.55	7.08	3.70	16.66	21.45	26.14	40.20	0.62	20.34	22.75	9.48

Relationship between Twitter Sentiment Score and % women in the board

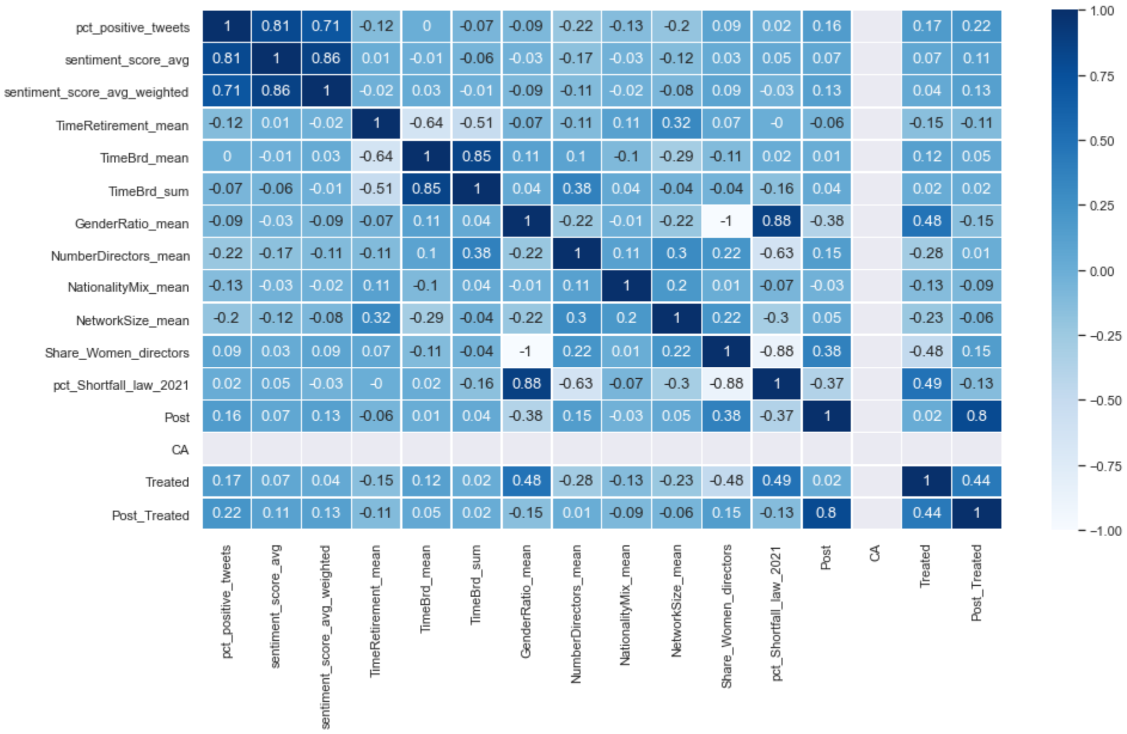
Supplementary Table 9. Evolution of share of women and twitter sentiment score between Treated and Control group

		Share_Women_directors		pct_positive_tweets		sentiment_score_avg		sentiment_score_avg_weighted	
	Treated	**0.0**	**1.0**	**0.0**	**1.0**	**0.0**	**1.0**	**0.0**	**1.0**
Region	**Year**								
California	**2016**	27.11	14.49	59.85	62.83	0.19	0.17	0.19	0.18
	2017	31.31	15.43	60.31	64.24	0.17	0.18	0.19	0.19
	2018	33.93	16.84	67.14	69.41	0.22	0.21	0.23	0.23
	2019	34.27	21.93	64.18	69.88	0.19	0.22	0.23	0.23
	2020	35.31	26.26	64.89	69.31	0.18	0.20	0.22	0.22
	2021	34.91	30.21	62.90	69.90	0.15	0.21	0.18	0.23
non_California	**2016**	25.01	12.95	58.56	64.78	0.17	0.16	0.17	0.16
	2017	26.57	15.85	58.40	66.42	0.14	0.18	0.17	0.21
	2018	31.93	15.41	65.32	70.08	0.20	0.20	0.22	0.23
	2019	34.26	17.94	65.35	71.34	0.19	0.23	0.22	0.25
	2020	36.10	22.85	62.77	70.62	0.17	0.21	0.21	0.25
	2021	37.69	27.41	63.23	68.37	0.18	0.21	0.23	0.22

Supplementary Figure 5. Correlation matrix with California companies.



Supplementary Figure 6. Correlation matrix with non-California companies.



Regression Results

Supplementary Table 10. Regression 1: DiD for non-California companies.

OLS Regression Results

Dep. Variable:	Share_Women_directors	**R-squared:**	0.488
Model:	OLS	**Adj. R-squared:**	0.474
Method:	Least Squares	**F-statistic:**	35.37
		Prob (F-statistic):	1.72e-34
		Log-Likelihood:	-939.52
No. Observations:	268	**AIC:**	1895.
Df Residuals:	260	**BIC:**	1924.
Df Model:	7		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
const	30.7333	1.494	20.574	0.000	27.792	33.675
Treated	-15.4783	1.976	-7.833	0.000	-19.369	-11.587
v_2019	2.9867	2.112	1.414	0.159	-1.173	7.146
v_2020	3.8100	2.112	1.804	0.072	-0.350	7.970
v_2021	6.5267	2.112	3.090	0.002	2.367	10.686
v_2019_Treated	-0.9571	2.802	-0.342	0.733	-6.475	4.561
v_2020_Treated	3.1760	2.802	1.133	0.258	-2.342	8.694
v_2021_Treated	4.6483	2.893	1.607	0.109	-1.048	10.344

Omnibus:	7.207	**Durbin-Watson:**	0.865
Prob(Omnibus):	0.027	**Jarque-Bera (JB):**	7.227
Skew:	-0.402	**Prob(JB):**	0.0270
Kurtosis:	3.040	**Cond. No.**	13.1

Supplementary Table 11. Regression 2.1.1b Full Results Fixed Effects and Pooled OLS

PanelOLS Estimation Summary

Dep. Variable:	pct_positive_tweets	**R-squared:**	0.0602
Estimator:	PanelOLS	**R-squared (Between):**	-0.0528
No. Observations:	776	**R-squared (Within):**	0.0602
		R-squared (Overall):	-0.0310
		Log-likelihood	-2352.5
Cov. Estimator:	Unadjusted		
		F-statistic:	40.488
Entities:	165	**P-value**	0.0000
Avg Obs:	4.7030	**Distribution:**	F(1,632)
Min Obs:	0.0000		
Max Obs:	24.000	**F-statistic (robust):**	40.488
		P-value	0.0000
Time periods:	6	**Distribution:**	F(1,632)
Avg Obs:	129.33		
Min Obs:	114.00		
Max Obs:	140.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	60.496	0.7378	81.997	0.0000	59.048	61.945
Share_Women_directors	0.1845	0.0290	6.3630	0.0000	0.1276	0.2415

PanelOLS Estimation Summary

Dep. Variable:	pct_positive_tweets	**R-squared:**	0.0048
Estimator:	PanelOLS	**R-squared (Between):**	-0.0157
No. Observations:	776	**R-squared (Within):**	0.0334
		R-squared (Overall):	-0.0024
		Log-likelihood	-2281.7
Cov. Estimator:	Unadjusted		
		F-statistic:	3.0008
Entities:	165	**P-value**	0.0837
Avg Obs:	4.7030	**Distribution:**	F(1,627)
Min Obs:	0.0000		
Max Obs:	24.000	**F-statistic (robust):**	3.0008
		P-value	0.0837
Time periods:	6	**Distribution:**	F(1,627)
Avg Obs:	129.33		
Min Obs:	114.00		
Max Obs:	140.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	63.514	0.8861	71.678	0.0000	61.774	65.254
Share_Women_directors	0.0613	0.0354	1.7323	0.0837	-0.0082	0.1308

Supplementary Table 12. Regression 2.1.2b Full Results Fixed Effects and Pooled OLS

PanelOLS Estimation Summary

Dep. Variable:	pct_positive_tweets	**R-squared:**	0.0825
Estimator:	PanelOLS	**R-squared (Between):**	-0.0642
No. Observations:	1677	**R-squared (Within):**	0.0926
		R-squared (Overall):	0.0099
		Log-likelihood	-5257.6
Cov. Estimator:	Unadjusted		
		F-statistic:	46.692
Entities:	189	**P-value**	0.0000
Avg Obs:	8.8730	**Distribution:**	F(3,1557)
Min Obs:	0.0000		
Max Obs:	72.000	**F-statistic (robust):**	46.692
		P-value	0.0000
Time periods:	6	**Distribution:**	F(3,1557)
Avg Obs:	279.50		
Min Obs:	255.00		
Max Obs:	302.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	64.780	0.6700	96.693	0.0000	63.466	66.095
Share_Women_directors	0.0342	0.0282	1.2125	0.2255	-0.0211	0.0894
Share_Women_directors_Female	0.1140	0.0134	8.5085	0.0000	0.0877	0.1402
Share_Women_directors_Male	-0.0368	0.0131	-2.8228	0.0048	-0.0625	-0.0112

PooledOLS Estimation Summary

Dep. Variable:	pct_positive_tweets	**R-squared:**	0.0181
Estimator:	PooledOLS	**R-squared (Between):**	-0.0346
No. Observations:	1677	**R-squared (Within):**	0.0510
		R-squared (Overall):	0.0181
		Log-likelihood	-6382.5
Cov. Estimator:	Unadjusted		
		F-statistic:	10.257
Entities:	189	**P-value**	0.0000
Avg Obs:	8.8730	**Distribution:**	F(3,1673)
Min Obs:	0.0000		
Max Obs:	72.000	**F-statistic (robust):**	10.257
		P-value	0.0000
Time periods:	6	**Distribution:**	F(3,1673)
Avg Obs:	279.50		
Min Obs:	255.00		
Max Obs:	302.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	66.785	0.6615	100.95	0.0000	65.488	68.083
Share_Women_directors	-0.0272	0.0286	-0.9504	0.3420	-0.0833	0.0289
Share_Women_directors_Female	0.0731	0.0248	2.9448	0.0033	0.0244	0.1217
Share_Women_directors_Male	-0.0645	0.0244	-2.6459	0.0082	-0.1123	-0.0167

Supplementary Table 13. Comparison of Fixed Effects and Pooled OLS for Regression 2.2.1

Model Comparison

	Fixed Effects I	Fixed Effects II	Pooled
Dep. Variable	pct_positive_tweets	pct_positive_tweets	pct_positive_tweets
Estimator	PanelOLS	PanelOLS	PooledOLS
No. Observations	536	536	536
Cov. Est.	Unadjusted	Unadjusted	Unadjusted
R-squared	0.0012	0.0015	0.0062
R-Squared (Within)	0.0012	-0.0056	-0.0086
R-Squared (Between)	0.0011	-0.0055	0.0043
R-Squared (Overall)	0.0027	-0.0053	0.0062
F-statistic	0.4564	0.6065	3.3072
P-value (F-stat)	0.4997	0.4366	0.0695
=====================	=====================	=====================	=====================
const	67.424	66.023	69.111
	(76.545)	(61.657)	(52.043)
Share_Women_directors	-0.0217	0.0306	-0.0847
	(-0.6756)	(0.7787)	(-1.8186)
======================	======================	======================	======================
Effects	Entity	Entity	
		Time	

Supplementary Table 14. Regression 2.2.2 Pooled OLS and Fixed Effects.

PanelOLS Estimation Summary

Dep. Variable:	pct_positive_tweets	R-squared:	0.0086
Estimator:	PanelOLS	R-squared (Between):	0.0148
No. Observations:	536	R-squared (Within):	0.0086
		R-squared (Overall):	0.0290
		Log-likelihood	-1478.4
Cov. Estimator:	Unadjusted		
		F-statistic:	1.7013
Entities:	164	P-value	0.1838
Avg Obs:	3.2683	Distribution:	F(2,393)
Min Obs:	0.0000		
Max Obs:	16.000	F-statistic (robust):	1.7013
		P-value	0.1838
Time periods:	4	Distribution:	F(2,393)
Avg Obs:	134.00		
Min Obs:	122.00		
Max Obs:	140.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	68.405	1.0484	65.247	0.0000	66.344	70.466
Share_Women_directors	-0.1418	0.0770	-1.8420	0.0662	-0.2932	0.0095
Treated_Share_Women_directors	0.1452	0.0846	1.7158	0.0870	-0.0212	0.3117

PanelOLS Estimation Summary

Dep. Variable:	pct_positive_tweets	R-squared:	0.0128
Estimator:	PanelOLS	R-squared (Between):	0.0136
No. Observations:	536	R-squared (Within):	-0.0004
		R-squared (Overall):	0.0277
		Log-likelihood	-1473.1
Cov. Estimator:	Unadjusted		
		F-statistic:	2.5205
Entities:	164	P-value	0.0817
Avg Obs:	3.2683	Distribution:	F(2,390)
Min Obs:	0.0000		
Max Obs:	16.000	F-statistic (robust):	2.5205
		P-value	0.0817
Time periods:	4	Distribution:	F(2,390)
Avg Obs:	134.00		
Min Obs:	122.00		
Max Obs:	140.00		

Parameter Estimates

	Parameter	Std. Err.	T-stat	P-value	Lower CI	Upper CI
const	67.052	1.1729	57.166	0.0000	64.746	69.358
Share_Women_directors	-0.1107	0.0777	-1.4239	0.1553	-0.2635	0.0421
Treated_Share_Women_directors	0.1789	0.0850	2.1046	0.0360	0.0118	0.3461

Why use Panel Data?

Panel data is formed by taking into account the same cross-sectional units over multiple time points. Since, in a panel dataset, there are multiple observations of the same entities, unobserved characteristics can be controlled and the results are much more powerful than regular one cross-section or time-series datasets in determining causal inference. Hence, panel data allows to deal with unobserved heterogeneity and resulting endogeneity leading to biassed results.

The data obtained in the methodology is panel data since for each company there are several observations of the Twitter sentiment score (daily, monthly and yearly time-span) and of the share of women in the board (yearly time-span).

There are several types of Panel Data Regression:

- **PooledOLS** is a simple OLS (Ordinary Least Squared) model that uses panel data while ignoring time and entity characteristics and focusing on dependencies between the same entities. Nonetheless, PooledOLS is not an appropriate model for Panel Data
- **Fixed-Effects (FE) Model** disregards the fact that there are differences in average level of the dependent variable for each entity and it assumes that those differences correspond to entity-specific characteristics that are stable over time. Hence, Fixed Effects focuses on dependencies within same entities, in this case controlling for the firm and year
- **Random-Effects (RE) Model** focuses on dependencies within and between entities.