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Does Board Gender Diversity Affect Inventor Productivity?

A comparison of inventor productivity before and after enactment of gender quota mandate on boards of publicly listed companies in Norway

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Abstract

Norway was the first country to mandate a gender quota for corporate boards of publicly listed firms. This quota mandates that publicly listed companies in Norway must have 40% representation of each gender on the board of directors. We analyze the effect, if any, of the 2003 regulatory change on the innovative productivity of inventors in Norway. The regulation was enacted for all publicly listed companies in Norway on 15. August 2007 and required non-abiding firms to be disbanded. Firms' research and development efforts rely heavily on problem-solving; creating the best possible premise for this is critical. Previous studies have shown that a broader composition of development teams, for example a better gender balance, improves team performance. We research whether the regulatory change requiring more female directors affected inventor teams and female inventor productivity. We employ fixed effects ordinary least squares regression on a sample with 5,218 unique patents by 6,906 inventors from 1995 to 2014. We find no significant impact of the regulation on Patent Count or Citation-Weighted Patent Count for inventors employed by listed or unlisted firms. This finding is in agreement with previous literature, which is characterized by ambiguous results and non-significant coefficients signaling a minimal impact of the regulation on innovation and financial measures.

Keywords – Innovation, Patents, Citations, Gender Quota, Board of Directors

Contents

List of Figures

List of Tables

1 Introduction

1.1 Background and Motivation

Innovation lies at the heart of economic growth and competitiveness, driving technological advancement, organizational development, and broad market adaptations. Establishing innovative corporate cultures has become increasingly important in the global business landscape, characterized by relentless competition (Urbancova, 2013). It is increasingly evident that teams striving to create new inventions will not perform optimally if they are composed of individuals with homogenous backgrounds, educations, age, and gender, among other factors (Miller & Del Carmen Triana, 2009). Facilitating higher degrees of diversity within teams can be vital in exploring complex challenges and seeing the same issue from alternative perspectives (Bantel & Jackson, 1989).

Exploring the influence of diversity on the financial performance of firms has been the subject of previous research (Ahern and Dittmar (2012); Bennouri et al. (2018); Shrader et al. (1997); Dezsö and Ross (2012)). We wish to take a different approach in determining its impact on firms. Innovation is vital for establishing and keeping competitive advantages in a constantly evolving business landscape, and thus, the rationale is to maximize innovative productivity at the firm- and individual inventor level. The total firm's innovative productivity is a result of the productivity of each individual inventor within the company.

In recent decades, there has been a surge in the pursuit of diversity, emphasizing equal opportunities between genders, ethnicities, and ages, among other factors. Historically, the business landscape has had a pronounced masculine bias, compelling some women to downplay feminine traits and strengthen masculine traits to win votes for seats on corporate boards or even withdraw from the competition (Claringbould & Knoppers, 2007). This creates an argument for mandating gender balance in places where diversity might be essential (significant decisions requiring difficult problem-solving). Nonetheless, these mandates do not come without controversies, with a prominent counterargument contending that the pursuit of gender balance may lead to the oversight of highly qualified candidates, thereby reducing the overall effectiveness of the entity. Several jurisdictions have already imposed such mandates, allowing researchers to investigate their impacts on affected firms and employees.

The composition of a board is a critical element. Ensuring the presence of well-suited individuals in key positions is essential for making superior decisions that give a competitive edge. The fundamental function of the board itself – assuring that the interests of the firm's shareholders are upheld – can be argued to be inherently biased towards short-term profits and increases in share price. The board is constantly challenged between chasing safer, short-term gains or delving into riskier long-term projects of research and development (R&D) and innovation. In this context, an argument emerges for optimizing board members' attributes and characteristics, aligning them with the organization's strategic focus.

In 2003, the Norwegian government mandated that all publicly listed companies represent at least 40% of each gender on the board. Acknowledging that diversity, characterized by a range of backgrounds and experiences, plays an essential role in fostering effective problem-solving and driving innovation, it is possible to research how and if this regulation affected companies performance through two main channels: better decision-making in the boardroom, and a higher degree of gender diversity throughout the companies. We will focus on the latter, turning our attention towards individual inventors within the companies. In this thesis, we define "inventors" as the unique people participating on patents in companies. Additionally, we compare inventors based on gender to see if the regulation brought trickle-down effects to female inventors. In this thesis, we suggest the following research question:

Did Norway's gender diversity regulation for corporate boards improve inventors' productivity and were female inventors particularly impacted?

1.2 Scope of the Thesis

This thesis aims to expand upon the work of Griffin et al. (2021) and incorporate methods from Moretti (2021) while focusing on inventor-level productivity in the context of a unique natural experiment in Norway. While Griffin et al. (2021) explored the impact of female board representation on firm innovation, our study narrows its focus to examining a quasi-natural experiment's effect on individual inventors. We also consider the nuanced perspective of Adams and Ferreira (2009), exploring the complex relationship between gender board composition, corporate governance, and firm performance. Our research relies on patent data from Norway from 1995 to 2014, ensuring a precise and detailed examination of inventor-level productivity.

1.3 Thesis Content

The thesis is structured in the following way:

Chapter 1 describes the background, motivation, and objectives of the thesis.

Chapter 2 introduces the literature upon which this thesis is based.

Chapter 3 presents the methodology used to examine the research question empirically.

Chapter 4 conveys the choices made during data handling and sample creation.

Chapter 5 presents the results and discusses findings, robustness, and limitations

Chapter 6 concludes this thesis.

2 Literature Review

This literature review will introduce key studies which provide a background for our study and present the research gap we intend to fill. We begin with an introduction of the current research regarding innovation and drivers of innovation. Second, we look at studies investigating diversity in the workforce and the impact of diversity on company performance and innovation. Third, we assess diversity in the board of directors and introduce channels through which this may impact the broader organization. Fourth, we present a measure of innovative productivity and quality and substantiate this with previous use cases. We then introduce the characteristics of Norway that serve as the basis for exploring the topic, only to delve into why a mandate might be necessary/productive. Lastly, we briefly examine the flipside and the possible adverse effects of forcing a mandate on publicly listed firms.

2.1 Innovation and Drivers of Innovation

Innovation has been defined simply as “a new idea, method, or device” or as “the introduction of something new” (Merriam-Webster, 2023). However, we often refer to the innovation process in the corporate world. In an attempt to characterize the process of innovation, Damanpour and Schneider (2009) underline the complexity of the process, while Griffin et al. (2021) stress the importance of R&D expenditures, resource commitment, and prolonged periods of uncertainty and risk.

Innovative performance is crucial to firms, as it lays the foundation for the firm’s growth and value creation. Kogan et al. (2017) find a robust positive association between the number of patent citations and firms’ market values. The authors also find that firm growth is closely related to the rate of innovation, mainly through varieties of products and the overall product quality. Understandably, firms seek channels to improve their innovative performance.

Taalbi (2017), in his analysis of the Swedish manufacturing industry, identifies four different factors behind innovation. He proposes that innovation is often problem-driven (1), as innovation usually has the motivation to solve a problem. Additionally, he segments the factor “opportunity-driven” into two factors, namely market opportunities (2) and technological opportunities (3). Lastly, he states that innovation can be based on an institutionalized search (4). Hence, the factors affecting innovation form a complex environment of confounding variables.

2.2 Diversity in the Workforce and its Impact on Performance

Cao et al. (2021) find strong evidence to suggest that board diversity is positively associated with innovation outcomes. The authors find that board members are able to leave their mark on corporate innovation by influencing the firm's inventors. Additionally, they find that including directors of minority backgrounds on the boards attracts more minority employees and promotes collaboration among inventors.

A link between diversity and creativity has been established by Stahl et al. (2010). They argue through a meta-analysis of empirical studies of team processes and performance that increased cultural diversity in teams increases creativity and satisfaction. Although this is not a direct connection between diversity and innovation, it is not unlikely to assume that larger diversity contributes to more innovation.

Through a systematic review of studies concerning the impact of board gender diversity on financial performance, Hazaea et al. (2023) found that there was inconsistency in the effects of gender diversity on financial performance, "as some studies confirmed the existence of a direct impact, while others showed the absence of a direct impact." The authors' conclusion implies that for gender diversity to improve financial performance, there must be certain underlying factors related to the company's environment and organizational setup already in place.

Croson and Gneezy (2009) propose that fundamental differences between psychological characteristics in men and women affect decision-making in the corporate world. Most importantly, they find that women (who tend to be more risk-averse than men) are more likely to possess a long-term view of situations, keep faith in decisions longer, and are less likely to suffer from overconfidence.

Research on the relationship between diversity and group performance produces conflicting perspectives. Watson et al. (1993) suggest that diversity leads to a more extensive knowledge base, creativity, and innovation which becomes a competitive advantage. Furthermore, Bantel and Jackson (1989) found that greater education and functional background diversity in top management teams led to better strategic decision-making. These findings were further substantiated by Pelled (1996).

Adams and Ferreira (2009)'s findings contradict the positive findings previously mentioned. They find that gender diversity is negatively linked to firm performance. The authors argue that these results suggest that mandating gender quotas for the board of directors can reduce firm value for well-governed firms. Depending on board performance before any mandates, the mandate's effect could positively or adversely affect the firm.

Long-term incentives for management are essential to consider in the case of R&D and innovation. Griffin et al. (2021) find that board gender diversity is associated with a higher fraction of CEO noncash pay, typically more long-term, which incentivizes long-term commitments. Additionally, they find that the proportion of female directors is significantly linked to the quality of patents produced by the firm. Dezsö and Ross (2012) further substantiate this effect on corporate innovation by promoting a more diverse labor force through an increase in board diversity, which we will explore further in Section 2.3.

Erhardt et al. (2003) present three studies (Hambrick et al. (1996); Knight et al. (1999); Treichler (1995)) in which top-management diversity was found to be a disadvantage in terms of group performance. All papers reach similar conclusions related to heterogenous top-management teams, on average, being slower to respond to competitors' initiatives. This slow rate of response can be particularly detrimental in fields characterized by high market competition. The authors suggest that this is due to the team's heterogeneous nature and that individuals were more likely to disagree and spend more time reaching agreement. Murray (1989), as cited by Erhardt et al. (2003), found that performance and diversity are related to the market type the organization operates in. Homogenous groups were more effective during intense market competition, while heterogenous groups were more effective in dealing with organizational change, complementing the findings mentioned above.

Bennouri et al. (2018) dispute the conclusiveness of the literature regarding gender diversity on corporate performance. They cite previous research with both positive and negative effects and find that the attributes of female directors (such as their education level, business background, and experience) significantly impact a firm's financial performance in the form of return on assets (ROA) and return on equity (ROE). Their study finds similarly ambiguous results, as accounting-based performance measures such as ROA and ROE increase with female directorship. In contrast, market-based performance measures decrease with female directorship.

2.3 How Board Diversity Impacts the Overall Organization

The most significant contribution to research on board gender diversity and corporate innovation comes from Griffin et al. (2021). Through a vast dataset across 45 countries, they posit that board gender diversity affects firm innovation in three ways. First, by setting managerial contracts that incentivize innovation through a long-term focus of effort. Second, by fostering an innovative corporate culture. Third, by increasing diversity among inventors (previously established by Adams and Ferreira (2009)).

"Board functioning is highly related to organizational functioning" (Zahra and Pearce, 1989), as cited by Erhardt et al. (2003). Boards are commonly the most influential actors in determining firms' strategic direction while fulfilling a critical monitoring role for shareholders. "... because strategic decision-making is crucial for boards of directors, it seems logical to expect that organizations with higher levels of the board of director diversity will demonstrate higher levels of performance than organizations with less diverse executive boards" (Erhardt et al., 2003, p. 105).

Management theories suggest that diverse (including gender-diverse) boards can positively affect corporate innovation, as minority members are more likely to question "conventional wisdom" and the status quo (Johnson et al., 2015). This study suggests that increasing board diversity, including gender and background, may improve performance by facilitating different perspectives on the same issues.

Shrader et al. (1997) found a positive link between women (diversity) in management positions and firm financial performance. The authors suggested that the companies recruited from a relatively larger talent pool, subsequently recruiting more qualified applicants regardless of gender. Further, Mattis (2000), cited by Erhardt et al. (2003)

indicates that the board should reflect the diversity of the firm's customer base and labor pool.

Dezsö and Ross (2012) find that female representation in top management improves firm performance due to informational and social diversity benefits to the management team, resulting in improved managerial task performance. This finding, however, is contingent on the extent to which the firm's strategy is focused on innovation. This suggests that an overall firm strategy focusing on innovation may increase the impact of gender-diverse boards. Furthermore, the diversity of board directors is associated with a breadth of perspectives and conflict (Erhardt et al., 2003). Conflict was in this regard viewed positively because it allows for a broader range of opinions to be considered.

Post and Byron (2015) found in a meta-analysis of 140 studies that study at the relationship between women on boards and financial performance that the relationship is stronger in countries with more robust shareholder protection. Shareholder protection means that corporate governance is strong in the company through board members facing accountability for their actions and recommendations. For companies operating in countries with strong legal systems, diversity among board members seems more valuable as there is a large incentive to share perspectives and listen to all ideas.

Hazaea et al. (2023) conclude that the agency and resource dependence theories may be the most important theories explaining the relationship between gender diversity and financial performance. Agency theory concerns the relationship between the principal (shareholder) and agent (company executives) (Kopp et al., 2023), where Hazaea et al. (2023) propose that "gender diversity may enhance competition" and that "this enhances and contributes to improving the quality of decision-making and the overall performance of the company" Yasser, (2012) as cited by (Hazaea et al., 2023).

Regarding agency theory, the authors propose that board independence might be improved by increasing gender diversity as it allows for different viewpoints that might strengthen independence (Dwaikat et al., 2021) as cited by Hazaea et al. (2023). In relation to the resource dependency theory, which affirms the company's survival and continuity as dependent on external factors, Hazea et al. (2023) found that the diversity of a firm's board was related to its external factors, ultimately supporting the link between female board presence and financial performance.

Gull et al., (2018) as cited by Hazaea et al. (2023) identified that gender diversity on corporate boards may introduce diverse perspectives, skills, knowledge, and values that can increase the company value for stakeholders. Additionally, Srivastava et al., (2018) as cited by Hazaea et al. (2023) find that diversity on corporate boards changes the dynamics within the group and displays heterogeneity during the decision-making process, increasing the number of differing viewpoints and opinions.

The appointment of female board directors may also positively affect the attendance and inherent effectiveness of the board. Adams and Ferreira (2009) find that female board representatives are 30% less likely to have attendance problems compared to their male counterparts. What's more, they find that "... the total number of male attendance problems is negatively and significantly related to the fraction of female directors" (Adams & Ferreira, 2009, p. 298). This implies that the presence of women on boards not only directly increases the attendance numbers through the female directors, but also affects these numbers indirectly as their male counterparts see an increase in attendance as well. This effect is further substantiated, as they find that women's increased attendance numbers are prominent regardless of the length of tenure, suggesting a pure gender effect and not simply a "newcomer effect" (Adams & Ferreira, 2009).

2.4 Number of Granted Patents as a Proxy for Innovative Productivity

Finding a quantifiable measure of innovation productivity is challenging. Innovation happens over many years, and patents have historically been used to measure innovation productivity (Griffin et al., 2021). Katila (2000) finds several studies suggesting that the number of citations is a good measure of the quality of innovation. Furthermore, the author finds evidence that citation-weighted patents are a valid measure of market disruption: a significant relationship between Citation-Weighted Patent Count (CWPC) and independent measures of economic value for these same innovations (Trajtenberg 1990) as cited by Katila (2000)). The logic is simple: the more citations a patent receives, the more impactful it is.

2.5 Norway as a Natural Experiment

Norway has used laws as a tool in its attempt to speed up the shift to gender equality in board representation, CEO positions, and corporations at large. Already in 1999, the topic of affecting gender equality in boards through laws was discussed. The topic first materialized through a modification in "likestillingsloven", Norway's law of equality. In 2003, likestillingsloven, § 2, condition e, was modified, now stipulating that all publicly owned and state-owned companies must adhere to at least 40% representation of both genders on boards (Regjeringen, n.d.). In 2023, the Norwegian government presented a proposal (Prop. 131 LS) which would see the mandate affect a number of privately owned companies as well. From 2024 to 2028 the government intends to make the 40% representation mandatory for privately owned firms who meet requirements related to size, revenues, and ownership structure (fiskeridepartementet, 2023).

Female representation in corporate boards has long been an element of discussion based on historically low participation rates. Norway was the first country to act politically on this issue by mandating gender balance in the boardroom (Bøhren & Staubo, 2014). Prior to 2004, publicly listed and private companies existed in Norway with relatively similar demands given by regulators concerning board composition. When the regulation was passed, only 9% of board seats were held by women (Ahern & Dittmar, 2012). The regulation required all publicly listed companies to have at least 40% representation of both genders on their boards by August 15^{th} 2007; otherwise, the firm would be forced to dissolve (Ahern & Dittmar, 2012). This regulation served as an exogenous shock and has been used as a quasi-natural experiment in previous research (Ahern and Dittmar (2012); Bøhren and Staubo (2014); Griffin et al. (2021))

The effects of the legislation on publicly listed companies has been substantial, particularly when comparing it to the statistics of privately owned companies. According to Statistisk Sentralbyrå (n.d.), the share of female board members in publicly owned companies rose from under 10% in 2004 to just over 35% in 2008 in Norway. On the other hand, the share of female board members rose from 15% to 17% in privately owned companies during the same period. From 2009 to 2023, however, the share of female board members rose from 40% to 43% in publicly owned companies, and from 17% to 20% in privately owned companies. Hence, There is no doubt in the mandate's effectiveness in increasing the share of female board members in public companies.

According to Post and Byron (2015), Norway is above average regarding the Shareholder Protection Index and leading regarding the Gender Parity Score (GPS). This suggests that Norway, particularly, might see a stronger effect regarding firm performance and innovation when increasing gender diversity in companies and boards. Although the EU has a high average GPS, equal representation of genders in research and innovation (R&I) proves difficult to attain (Striebing et al., 2020). These studies imply that mandating female board representation might positively impact female employees (Griffin et al., 2021). However, Striebing et al. (2020) have found that this may prove difficult in innovation-centric businesses due to differences in preference to work-life balance and career development.

2.6 Why Would a Mandate be Necessary?

Although some argue that "more diversity is better", one could counter this by asking why the market economy has not already optimized for more diversity if it was optimal. Claringbould and Knoppers (2007) find evidence that men can control boards by framing the recruitment process for new board candidates in such a way as to reproduce the male-dominated culture of the board. This finding is substantiated by Adams and Ferreira (2009). The authors also find that female board candidates tend to distance themselves from their gender to prove their "fit" (Claringbould & Knoppers, 2007). This is further substantiated by Mitra et al. (2021) who find that female board of directors' candidates receive, on average, fewer votes than male candidates. They also find that female candidates are evaluated more harshly than male candidates.

2.7 Possible Adverse Effects of a Mandate

Mandating gender balance on corporate boards limits the shareholders' free choice in selecting the best candidate, possibly resulting in directors with less experience (Eckbo et al., 2022). The authors point out that this can reduce the board's advice and oversight quality. Furthermore, Orlé (2023) studied the impact of a similar regulation in France and found no change in financial performance indicators before and after the change, signalling that the regulation has minimal actual impact on performance.

Ahern and Dittmar (2012) studied the differences in board members after the gender quota mandate in Norway. They found that the new female board members were significantly less likely to have CEO experience. In fact, only 31% of the new female directors had any prior CEO experience, whereas 69% of the retained male directors had prior CEO experience. They also found that the newly appointed female board members were significantly younger than the retained male directors; the average newly appointed female director was 8 years younger than the average retained male director. Ahern and Dittmar (2012) argue that personal characteristics such as age, education, and experience directly affect the board members' ability to monitor and advise the firm hence, a lack of these characteristics may adversely affect the firm's performance.

Reddy and Jadhav (2019) summarize possible drawbacks of mandating the representation of women on corporate boards. They point towards experience as a central factor in appointing any board member, consequently, some believe that the pool of female candidates with the appropriate experience is far smaller than that of male candidates. Another issue with mandating the appointment of female board members is that female candidates may get appointed to a board seat despite being the lesser of two candidates, simply to "fill the quota" (Reddy & Jadhav, 2019).

Adams and Ferreira (2009) find that adding female board representation in firms with strong corporate governance may reduce the firm's value. They acknowledge the value added through female bard representation but stress that it does not suggest support for quota-based policy initiatives. In fact, they suggest that proposals for enforcing gender quotas may be motivated by reasons other than improvements in governance and firm performance.

2.8 Key Contributions

Our work expands on the work done by Griffin et al. (2021), while employing methods from Moretti (2021) in the process. Whereas Griffin et al. (2021) briefly researched the effect of female board representation on the innovative quantity and quality of firms in Norway, we seek to contribute to the body of literature by researching the impact of the quasi-experiment on the individual (inventor) level. We expand on the research of Griffin et al. (2021) through a more thorough approach to the quasi-experiment, including relevant controls and robustness checks to substantiate the findings. Links have previously been made between diversity and firm performance (financially and innovatively) (Kogan et al., 2017). We wish to study whether this link connects to the inventor level. Moretti (2021) provides the foundation for the technical aspect of the regression.

The opposing view in this discussion will draw from the discoveries of Adams and Ferreira (2009). They suggest that gender board composition is a more complex issue than the "popular press" makes it out to be, suggesting that increased female board representation only benefits firms with weak corporate governance. They find that firms with strong corporate governance could ultimately see a decrease in shareholder value through the enforcement of gender quotas. Adams and Ferreira (2009) focuses on gender, corporate governance, and firm performance, but as substantiated by Kogan et al. (2017), firm performance, innovation, and market value are intertwined. The work of Adams and Ferreira (2009) underlines the opaqueness in results achieved when researching the impact of board diversity. This opaqueness is also present in our findings. Based on the literature presented, we suggest the following hypotheses to be tested:

Hypothesis 1: *Following the event date, the expected inventor productivity in listed firms increased.*

Hypothesis 2: *Following the event date, the expected quality of patents improved in listed firms.*

3 Methodology

This section will introduce the methodology and approach for the research. We will introduce the research design and the empirical methods proposed to study the research question. Next, we will detail the design of the main regression models before finishing with descriptions of further regression model specifications to limit bias in the results and improve validity and reliability.

3.1 Research Design

The research is designed as a quasi-experiment investigating how a regulatory change impacts employee inventors based on whether or not they are employed by publicly listed companies. The models are quantitatively applied to data concerning granted patents in Norway from 1995-2014. Based on the literature review, we will use the number of filed patents (that are later granted) per inventor per year as a proxy for innovation, as innovation is a nuanced and broad variable that can be challenging to measure in other ways. Additionally, we will expand this to include CWPC to account for the quality of produced patents.

3.2 The Regression Model

In this study, we will apply a multiple linear regression model to the data, allowing us to observe the effect of the independent variables on the dependent variables. A "linear regression model establishes the linear relationship between variables based on the line of best fit." (Beers et al., 2023). The ordinary least squares (OLS) method is the most commonly used method for establishing the linear relationship. We use the OLS estimator for several reasons. Firstly, it is widely used amongst economists and statisticians, allowing us to convey our results effectively. Additionally, so long as the assumptions of the model are fulfilled, it is unbiased and consistent.

$$y_i = \beta_0 + \beta_1 x_1 + \ldots + \beta_n x_n + u_i \tag{3.1}$$

Because we want to study correlations between patenting productivity and different variables in a panel data frame, we decided a regression model is the most applicable method (Beers et al., 2023) based on the examples of Griffin et al. (2021) and Moretti (2021). However, five criteria must be met for the regression results to be usable and without bias.

3.2.1 Criteria for an Unbiased Ordinary Least Squares Regression

Unbiased ordinary least-squares regression estimates can only be obtained when all assumptions are satisfied. First, we will briefly explain what it means that the calculations are biased. Next, we will introduce the assumptions underlying the OLS model. Lastly, we will explain how we reduce bias in the regression models applied in this thesis.

Qin (2019) explains the fundamentals of bias: "... the bias arises when the ordinary least squares (OLS) estimator is applied to an a priori constructed model in which a causal variable is postulated to be correlated with the error term" (Qin, 2019, p.81). In essence, a regression model is biased when the estimated coefficients on average do not equal the population parameters (Rohrer, 2022b). There will always be factors influencing the estimated coefficients from converging on the population parameters.

The four most common sources of bias are omitted variables, measurement error, simultaneity, and sample selection. If our model is biased, it means – for various reasons – that the results we are left with are inaccurate or fail to tell the complete story. Next, we introduce the five the assumptions for an unbiased OLS regression, before explaining in detail how we plan to eliminate bias from our models.

1. The model is linear in parameters
   (a) The model must be linear in parameters (α and β) but not in independent variables (X's). Linear, as in the power of one.
2. There is random sampling
   (a) The sample is randomly drawn from the population. As the sample size increases, the sample will converge on the population.
3. The conditional mean should be zero

   (a) The average value of the error term, given any values of the independent variables (X's), is equal to zero.

$$E(\hat{\beta}_1|X_1,\ldots,X_n) = \beta_1 \quad \text{only if} \quad E(u_i|x_i) = 0 \tag{3.2}$$

4. There is no perfect multicollinearity
   (a) There should be no perfect correlation between two or more independent variables.
5. There is homosecdasticity and no autocorrelation
   (a) The error terms in the regression model should all have the same variance. The variance should not increase or decrease along the regression line which would signify that heteroscedasticity (the variance of the errors is not consistent across observations) is present.

Through the model's design, we aim to comply with all the criteria for an unbiased OLS regression, especially the zero conditional mean assumption. The patent data is a selection of patent applications in the period 1995-2014, which were later granted, with no further limitations on the observations. This is, by design, a selective sample made to represent the broader population of all patent applications (which are later granted) throughout the world. In Section 3.10 we will explain the further steps to improve the external validity of our results, given that we study a specific country with its particular regulations and business practices.

Next, we will perform a variance inflation factor (VIF) test, to account for the possibility of multicollinearity. If there exists a high degree of multicollinearity between any of the independent variables, we remove the afflicted independent variables one at a time based on economic intuition until the concern no longer persists. Additionally, in the design of the model and choice of dependent/independent variables, we have largely accounted for the multicollinearity possibility by selecting characteristics that are less likely to correlate highly.

Heteroscedasticity of standard errors and autocorrelation within groups threatens the accuracy of estimated standard errors in our models. Given that we are studying panel data which tracks the same individuals over time, there will likely be autocorrelation individuals within the same groups (Columbia, 2016). Autocorrelation means that there is a high degree of correlation between time series observations of a variable. For example, patent productivity in one year might be highly correlated to productivity in the previous year. In this case, not accounting for this means that there is a possibility of bias in the standard errors of the estimates, which will impact the t-statistics and p-values, potentially leading to incorrect conclusions. This is referred to as heteroscedasticity, where the standard errors are biased. We will apply heteroscedasticity robust standard errors to account for the possibility of heteroscedasticity. Furthermore, we will cluster these standard errors by organizations to account for additional correlation between inventors in the same organizations. Clustering standard errors reduces the potential correlation between standard errors by accounting for correlation within the same cluster (Abadie et al., 2017). Applying clustered standard errors is a simple way to account for correlation within clusters, as it will not have any impact on the regression in the absence of correlation in errors within organizations.

The zero-conditional mean assumption is the most problematic assumption we are facing. First, this assumption asserts that the model is not missing important variables in explaining the dependent variable (omitted variable bias). Next, the assumption will also be violated if simultaneity bias is present, which happens if the dependent variable and independent variable are causally linked to each other. For example, price is determined by demand, and demand is determined by price. Our models will include control variables and fixed effects to account for omitted variable bias. Because of the nature of the panel data we are researching, we can apply fixed effects to the regression models to remove unobservable characteristics that vary across entities but not over time (entity fixed effects) and unobservable characteristics that vary across time but not across entities (time fixed effects), explained further in Section 3.8.

Simultaneity is an unlikely threat, as the dependent and independent variables are not causally linked. For example, being a prolific inventor with many patents does not imply a specific gender or what type of firm the person works at, and the same goes for the opposite direction of causality. However, one could argue that the most productive inventors will self-select into companies that favor and invest heavily in R&D. Further, as many publicly listed companies have stock-option plans for employees, incentives may be better aligned to produce superior effort by the employee inventors. Additionally, it can be argued that the "prestige" of working at a publicly listed company may drive the most talented inventors there. We account for this possibility with the application of entity (inventor) fixed effects to remove unobservable inventor characteristics, such as personal motivation or drive to perform, to see the general effect on all inventors of the event we are studying.

For the regression results to be valid, the sample in question needs to be an accurate representation of the population. Failing this would mean that the zero conditional mean assumption is violated (Rohrer, 2022b) and the coefficients will be biased. The patent data in itself is believed to be an accurate representation of the population as no limitations are placed on it other than limiting it to patents filed in Norway. On the other hand, the citation data might violate this assumption, as it is an incomplete representation of the actual citations for patents filed in Norway. The sample contains no citations for patents filed before 2001. We do not believe this is an issue, however, as the period of analysis is primarily after the year 2004 where we have plenty of citation observations. The citation data and problem mitigation efforts will be discussed further in Section 4.1.2

3.3 Interpolating Zero-patent Years

An issue related to sample selection in the data is that inventors are present only in the years they apply for patents (which are later granted). Because we are studying inventor-level productivity, we have gathered inventor-year data, meaning that each inventor has one observation in each year they are producing patents. Using this data at face value would imply that each inventor is more productive than they really are, given that they are only in the sample in years they patent (upward bias of productivity). Our aim is to measure innovation, hence we need to account for all years the inventors are likely researching, not just the years in which the research proves fruitful. We will, therefore, interpolate zero-patent years between nonzero-patent years, as done by Moretti (2021). Below is an example of what the interpolation does to an individual inventor in the sample.

Before

Inventor ID	Year	Patent ID	Month	Patent Count
fl:aa_ln:coleman-1	2009	8601401	1	0,33
fl:aa_ln:coleman-1	2011	9182486	12	0,56
fl:aa_ln:coleman-1	2012	9223022	2	1,39
fl:aa_ln:coleman-1	2013	9298079	2	0,56

After

Inventor ID	Year	Patent ID	Month	Patent Count
fl:aa_ln:coleman-1	2009	8601401	1	0,33
fl:aa_ln:coleman-1	2010	NA	NA	0,00
fl:aa_ln:coleman-1	2011	9182486	12	0,56
fl:aa_ln:coleman-1	2012	9223022	2	1,39
fl:aa_ln:coleman-1	2013	9298079	2	0,56

Figure 3.1: Example of interpolation for one inventor.

Interpolating zero-patent years between years with patents reduces sample selection bias by keeping active inventors in the sample when they are likely working on patents but not applying for them. Without interpolating these values, the sample would include sample-selection bias with an upward direction in the Patent Count, as inventors are only in the sample when they patent (Moretti, 2021).

Not interpolating these values would also mean missing the effect of the regulatory change on the "probability of patenting (extensive margin)" (Moretti, 2021, p. 3338), as there would be no zero-patent years. The main model interpolation period has been defined as one year, and in Section 5.2 we will test whether the estimates are sensitive to different definitions of the interpolation period. As done by Moretti (2021), we will re-estimate the models using samples where the interpolation period is one year (baseline), two years, and three years. By estimating models using both short interpolation periods (one year) and long (three years), we can estimate and compare results when the missing zeros and downward bias in productivity are high (long interpolation period) and low (short interpolation period).

3.4 Log Transforming the Dependent Variable

We will logarithmically transform the dependent variable Patent Count, creating a Log-Lin (logarithmic-linear) OLS regression model to make the regression results more interpretable.

A Log-Lin regression specification has one key advantage: the main independent variable's impact on the dependent variable can be interpreted as $100 * \beta_D\%$ change in the dependent variable (Yuferova, 2023). This approach provides superior ease in interpretability, as it can be difficult to assess the impact of raw increases in Patent Count without extensive knowledge on patents and the typical rate of patents.

An important assumption of log transforming the dependent variable is that we have no negative or zero patent observations. As explained in section 3.3 we interpolate zero-patent years. By doing this, we insert zero-patent observations into the sample. This means we must apply a modification to the patent data in order to log-transform the dependent variable, as taking the logarithm of zero does not make sense.

$$\lim_{x \to 0^+} \log(x) \to -\infty \tag{3.3}$$

These observations are zero by design to include inventors (probably) researching something that would end as a patent application the following year. Hence, we believe it proves sensible to add a small and positive constant c to the Patent Count to run the log-transformed regression. We add a constant c to the Patent Count such that the left-hand side of the regression is as follows:

$$log(Patent\,Count + c) \tag{3.4}$$

$$log(Patent\,Count \times Citations + c) \tag{3.5}$$

Determining the size of the constant c is vital as it may adversely affect the accuracy of the regression results (Feng et al., 2014). Three common methods were proposed by different authors: adding a close to zero positive value, adding a value equal to half of the smallest nonzero value in the sample, and adding one to all observations (because log(1)=0).

Table 3.1: Summary of Patent Count variable.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0.0000	0.2000	0.3333	0.4885	0.5333	2.0000

Considering Equation 3.3, we believe adding an arbitrary decimal value close to zero might impact the outcome negatively. Likewise, considering Table 3.1, adding a one to Patent Count will negatively impact the results as the vast majority (more than 75%) of inventors-year observations have a lower than one Patent Count. We therefore use a constant c equal to half of the minimum observed nonzero value in the sample and add this to all Patent Count values.

$$c = \frac{min(Patent\,Count)}{2} \tag{3.6}$$

3.5 Why a Count Model is not Applicable

Using a count model (not to be confused with Patent Count) is not applicable in our case. In theory, an inventor has either produced zero or a whole number of patents per year. Applying the models at face value on the data in such a way would assume one patent for each participant on the patent team. This would grossly overestimate the number of patents per year and lead to biased coefficients, hence this method serves to treat teams of innovators in an unsuitable manner. In line with Moretti (2021), we calculate each patent participant's Patent Count (a fraction of the patent), which we explain in depth in Section 4.2.1. Employing this method means we now have decimal Patent Counts for many inventors; hence, the data is unsuitable for a count model regression (which requires whole positive numbers).

3.6 Measures and Tests for Significance

The R^2 is commonly used to quickly assess the fit of a model. Kennedy (2008) states that "R^2 ... represents the percentage of variation in the dependent variable 'explained' by variation in the independent variables" (Kennedy, 2008, p. 14). Hence, considering our analysis, the R^2 describes the percentage of variation in Patent Count explained by variation in the variables "Listed," "Female," and "Post," as well as control variables and fixed effects. However, some question the magnitude and subsequent relevance of R^2, particularly in a multiple regression model, as the R^2 will mechanically increase whenever a regressor is added (Stock & Watson, 2020). Yet, the R^2 is still commonly used by many to paint a picture of how well the regression model summarizes the relationship among different variables in a systematic approach. Notably, Kennedy (2008) stresses that there is no "generally accepted" standard of what a high R^2 is. Hence, the context of one's dataset and subsequent regression is important when interpreting it.

Kennedy (2008) continues, "... a high R^2 is not necessary for "good" estimates; R^2 could be low because of a high variance of the disturbance terms, and our estimate of β could be "good" on other criteria." (Kennedy, 2008, p. 27). Additionally, cross-sectional datasets tend to have low R^2 statistics, further lowering the importance we place on our R^2 values. This is not to say we discard the R^2 values as "unimportant", in fact the regressions in the main model have considerable values of R^2. They should, however, only be interpreted as pieces of a larger puzzle. An alternative to R^2 is looking at the adjusted R^2 value, as this does not mechanically increase with the addition of each new independent variable, hence the adjusted R^2 will always be lower than the R^2 (Stock & Watson, 2020, pp. 223-224). Notably, the adjusted R^2 is still similarly flawed, as it fails to explain any causality in the results.

To assess the significance of the coefficients produced in the regression, we use the p-value and subsequent t-values. The p-value is defined as "... the probability of drawing Y at least as far in the tails of its distribution under the null hypothesis as the sample average you actually computed" (Stock & Watson, 2020, p. 110). Hence, a p-value of 5% implies that the observed data would only be obtained five percent of the time if the null hypothesis (that the variable in question has no impact on the dependent variable) is true (Andrade, 2019).

Closely linked to the p-value is the t-statistic. The t-statistic is central to testing statistical hypotheses (Stock & Watson, 2020). For this specific model, we have employed "***," "**", and "*" to represent significance at the "1%", "5%", and "10%" levels, respectively. Suppose the "Listed" regressor is statistically significant. In that case, we can conclude that the coefficient of the independent variable is significantly different from zero, implying that if an inventor works in a listed firm, it will somewhat affect their innovative quantity or quality. To summarize, where the R^2 and adjusted R^2 measure the fit of a given model, the p-value and t-statistic indicate whether an independent variable is likely to affect the dependent variable. The t-statistic will be instrumental in assessing statistical significance in Chapter 5.

3.7 Difference in Difference Model

The quasi-experiment nature of the regulation creates a fitting environment to run difference in difference (DiD) regression models. The DiD specification allows for testing of the effect of treatment on the treated group compared to a control group with similar characteristics that did not receive treatment (Stock & Watson, 2020, p. 492). Because of the parallel trend assumption, we assume that each group would develop similarly without the event. The parallel trend assumption states that in the absence of treatment (event), the difference between the treated and the control groups is constant over time.

The regulation exclusively affected publicly listed companies in Norway, without any consideration for non-listed enterprises, allowing us to compare inventor productivity between the groups after the event date. This would imply that following the event date if there is no impact from the event, the difference between the groups should be constant. In Chapter 2, we established that previous studies used this event as a quasi natural experiment (Ahern and Dittmar (2012); Bøhren and Staubo (2014); Griffin et al. (2021)). This assumption allows us to study the event with reduced concerns for endogeneity in the independent variables (Bøhren & Staubo, 2014). To run a DiD regression model, we need to determine several key factors: the event date, and a treatment and control group that satisfy the parallel trend assumption.

3.7.1 Determining the Event Date

The process of identifying the event date will use the legislation on board gender composition as its foundation. The regulation concerning state-owned entities was set in motion from January 1st, 2004, with a two-year transition period where the firms could transition to new board compositions. For privately owned listed companies, the transition period would be from August 15th, 2005, and last for two years, effectively giving listed companies four years to comply with the regulation to avoid reprimands.

Due to the differences in the exact date when state-owned and listed firms needed to comply with the regulation, we use January 1st, 2004, as the event date. The firms did not have to comply immediately following this, but it can be expected that they initiated the gradual change to comply with the regulation. An implicit assumption from this in the interpretation of the models is that all listed firms after the event date have a minimum of 40% representation of each gender on the board (Regjeringen, n.d.). This will be wrong in many cases, as the firms needed several years to comply with the new regulation. We believe that the initial shock of the announcement put gender balance on the radar and started the transition to reach the 40% threshold. Hence, it proves the most accurate event date in relation to the research question. To assess these event date assumptions, we will modify the date and rerun models in Section 5.2.

3.7.2 Treatment and Control Group

The population we study is that of inventors. As we study a quasi-experiment in which the legislation only affected inventors working in Norwegian firms, our sample consists exclusively of such inventors. The treatment group is defined as inventors working in listed firms during the event study. This was chosen as the regulation in late 2003 only impacted publicly listed companies in Norway, and by extension, inventors working for listed firms and state-owned enterprises. Conversely, the control group is defined as all inventors working in non-listed firms during the event study. Inventors working for publicly listed companies are hence referred to as "treated inventors", while inventors working in private companies are "non-treated inventors."

We decide that performing a matching procedure, such as nearest neighbor or propensity score matching, to match treated inventors to similar non-treated inventors would create a key issue in the analysis. Most inventors (60%) file only one patent throughout the period, meaning that they are only observed once in the sample. Because we wish to study all inventors, regardless of them being high producers or not, we do not remove these once observed inventors from the main models. Subsequently, matching treated inventors to the most similar non-treated inventors proves ineffective, as there are too few inventors filing patents in several years. For example, we can match similar inventors before the event in year 2003 only to see that either the treated or control inventor disappears from the sample in the following year, removing any chance of comparison. To achieve greater clarity on the regulations impact on the most productive inventors, we will rerun the models on a reduced sample of inventors with greater than one observation in Section 5.2.

Additionally, self-employed inventors also fall into control group. Whereas previous studies on firm-level innovation have been forced to discard these from the sample, our classification allows for their inclusion, as we research the impact on the inventor level rather than the firm level. This means we can test whether the regulation had a trickle-down effect on inventors based on the ownership form of their employer.

3.7.3 Parallel Trend Assumption

The parallel trend assumption states that in the absence of treatment, the difference between the treated and control group should be constant over time (Rohrer, 2022a). We cannot test this assumption definitively, but we can assume that if the groups behave similarly before the event, they will likely behave similarly after the event as well (Rohrer, 2022a). For example, we include variables allowing us to test whether female inventors were adversely affected by the regulation compared to male inventors. As we observe in Section 4.1.1, the data regarding female inventors is limited, due to the small fraction of female inventors compared to male inventors (Figure B.8). Drawing conclusions based on this data alone could be subject to unobserved confounding variables or limited statistical significance. Arguments could also be made for systematic preferential treatment towards male inventors and patent applications with male participants (Huang et al., 2020).

Although the number of female inventors is smaller than male inventors, we believe they on average, have the same expected output given similar circumstances. Based on this, we assume that the parallel trend assumption for these groups hold. Additionally, because we study inventors based on their gender, the type of firm they work at, and whether not they are observed after the event date, a triple difference-in-difference-in-difference model appears in the main regression table (Female $\times$Post$\times$Listed). Because we intend to apply fixed effects, we believe the inventors in listed and non-listed firms would behave in the same way absent the event (parallel trends) as unobservable differences between them have been removed.

3.8 Fixed Effects

For further depth of analysis and robustness, we will employ both inventor (entity) and year (time) fixed effects to the regression models. Including inventor-fixed-effects into the model means we will account for unobserved characteristics that vary across inventors but not time. Examples of this could be age, gender, or ethnicity. These are constant or change at a steady rate over time. Time-fixed effects account for characteristics varying across time but not individual inventors (Stock & Watson, 2020). Examples of this include regulation and broad world events. These characteristics impact all inventors in the sample. This will allow us to tease out whether the variables we are researching have the same direction of impact across different model specifications.

Fixed effects will increase the robustness of our estimates because it will remove bias in the model from unobservable variables that might impact patenting productivity (Stock & Watson, 2020). By applying changing circumstances to the baseline model, we effectively remove omitted variable bias and thus end up with more robust results. Suppose the models with fixed effects applied shows the same direction of impact from the explanatory variables. In that case, it can be assumed that those results are accurate, given the sample upon which they are applied. Lastly, fixed effects reduces concerns surrounding the difference in unobservable characteristics between inventors in respective groups, a crucial feature considering our choice of not matching a control group to the treatment group.

3.9 Griffin and Moretti Regression Models

Griffin et al. (2021) ran an instrumental variable regression approach where the authors employed the methods of Ahern and Dittmar (2012) and Eckbo et al. (2022). This approach uses the female director ratio as the main independent variable for firm-level innovative productivity. The authors use a two-stage least squares (2SLS) regression by instrumenting the female director ratio to address possible endogeneity concerns with the independent variable. We assume all listed firms comply with regulations and gradually increase the female director ratio following the event date.

Moretti (2021) employed an OLS- and IV-regression to measure the effect of cluster size on inventor productivity. Moretti's method entails using a 2SLS regression by instrumenting cluster size on the productivity of the inventor, which serves to allay concerns about endogeneity (an independent variable correlating with the error term) (Stock & Watson, 2020). We have chosen a DiD approach rather than IV, hence Moretti (2021)'s approach to reducing sample selection bias through interpolation proves most relevant to this thesis.

Since we analyse the inventor level, just like Moretti (2021), we adapt his interpolation method to our analysis, adjusting it accordingly to ensure robustness in our results.

3.10 Validity and Reliability

The data is assumed to be internally valid and reliable. The internal validity of our research will depend on whether the (potential) change in patenting productivity following the legislation can be attributed to the event. Due to the quasi-experiment nature of this thesis, there are likely confounding events and factors that will impact the results. To account for this, we have applied year-fixed and inventor-fixed effects which will remove unobservable factors varying across inventors and across time, consequently providing a clear treatment effect.

Furthermore, we argue that the results achieved are externally valid. This entails that the results achieved from our analysis of inventors working at listed firms can be applied to any other sample of inventors, given the circumstances are similar. Since we analyse a control group and treatment group consisting of inventors working at Norwegian firms, while controlling for fixed effects and a number of variables, any results achieved are likely applicable to samples fulfilling the same criteria. The event, and our study of this event, is hence relevant to legislators contemplating similar jurisdictional changes.

4 Data

This section will outline the data analysis, from gathering data to combining samples and creating variables. Section 4.1 will introduce the sources of data and how these were adjusted to fit together. Second, Section 4.2 will detail the variables used in the regression models. Next, Section 4.3 will elaborate on the the assumptions made with the data, the reasoning behind these, and the limitations we believe might affect the results. Lastly, Section 4.4 presents and overview of the data with summary statistics of key variables of interest.

4.1 Sample Creation

We use patent data from PatentsView, United States Patent and Trademark Office (USPTO) and corporate-financial data from Samfunns- og næringslivsforskning AS (SNF). The data from USPTO covers patents filed in Norway for coverage in the US. This automatically excludes some patents filed in Norway but not the US. Patentstyret, the Norweigan body of patenting, gives an indication of the patentability (likelihood of being granted) around the world (US, among others) to patent applications Patentstyret (2016). As inventors of quality inventions will likely want to protect their invention as much as possible, we assume that the patents not filed for in the US did not get a recommendation by Patentstyret. Hence, they were not of sufficient quality and specificity to get granted in the US.

We have used the programming language R and several packages for all basic data handling and further analysis. We have used the Tidyverse, DescTools, and data.table packages for syntax and data manipulation (Wickham et al. (2019); Signorell et al. (2023); Dowle et al. (2023)). For the regression models, including presentation, robust standard errors, and fixed effects, we have applied the PLM, fixest, lmtest, and Stargazer packages (Hlavac (2022); Croissant and Millo (2008); Zeileis and Hothorn (2002); Berge et al. (2023)).

Table 4.1: Overview of the data treatment process.

Step	Action	End Sample size
1	Complete patent data before combining and interpolation	14,549 observations with 6,165 unique patents
2	Combining observations to create inventor-year data with one observation per inventor per year they produced a patent	11,343 observations with 5,218 unique patents
3	Interpolating the inventor-year data (1-year period)	12,328 observations
4	Merging with citation data	12,328 observations, of which 4,204 have citations
5	Merging with financial data	12,328 observations, of which 10,374 have complete financial data
6	Merging with company data	12,328 observations, of which 9,196 have complete company data

4.1.1 Patent Data

From PatentsView we downloaded and combined multiple data sets to create a sample with detailed information on all patents granted in Norway in the period 1995-2014, including information on patent participants (names and gender), the organization by which the application was filed, and city of application. Next, we created the main independent and dependent variables before creating the inventor-year data. To create the inventor-year data, we combined observations such that each inventor only had one observation every year, summing the number of patents, and keeping the most common observations for other variables such as organization and location. In cases where inventors produced patents for multiple companies in a year with no "most common" company, the organization and subsequent location were chosen randomly.

A crucial decision is whether to use the date of patent filing or the date of the patent grant as the basis for the regression. The prevailing practice favors the filing date, as it most accurately captures the moment an inventor is actively engaged in the innovation process (Moretti, 2021). We are able to use the filing date as an accurate measure of innovation, since the sample only includes patents that were later granted, hence the sample is not plagued by patents that were filed without being granted later. Furthermore, relying on the date of patent granting poses challenges due to the lengthy and variable duration of the granting process, which often spans multiple years. Moreover, we found that patents filed in consecutive years may be granted at significantly different times, compromising our analysis's accuracy and validity, particularly as we interpolate the data. We, therefore, believe that the filing date for patents granted between 1995 and 2014 best captures the immediate distinctions between the treatment and control groups following the event date.

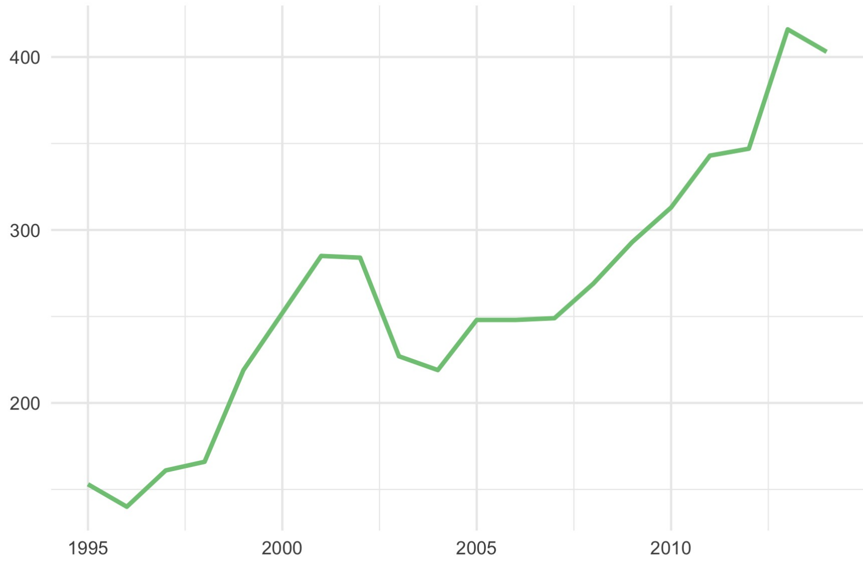

Figure 4.1: Annual Patents Applied for in Norway (1995-2014).

4.1.2 Citation Data

This section explains the citation data and the characteristics of the resulting sample after merging with the patent data. The citation data includes "citations made to foreign patents by US patents" (PatentsView, n.d.). Although this dataset is limited to US patent applications citing foreign patents, it includes citations for 2,205 of the 6,105 unique patents in our sample. After checking citation data from Zenodo (an open repository allowing researchers to deposit papers, data sets, reports, etc.), we conclude that PatentsView is the most complete citation data for our patent sample (Zenodo only included 385 of the 6,105 unique patents in our sample).

A general limitation with using the number of patents as a proxy for innovation is that we are not capturing the quality of the produced patents and their subsequent business impact. Previous studies have used patent citations to measure produced patents' subsequent impact and importance (Moretti, 2021). To account for this limitation, we include citation data from PatentsView to create a Citation-Weighted Patent Count (CWPC) to capture the quality of produced patents. What happens with patents that are not represented in the citation data or do not receive any citations is worth mentioning here. As citations only appear in the sample when the number is greater than zero, the result is NA citation count for all patents that are not represented in the citation sample. We changed this to zero instead for affected patents to keep these in the main analysis models.

The citation data includes citations for 2,205 out of the 6,105 unique patents in the sample, however these observations are clearly skewed regarding distribution in time. Analysis of the citation data sample (as illustrated in the graph below) revealed that the citation dataset did not reference patents from the patent sample before 2001. Intuitively, patents granted earlier have several years more to be cited than patents filed late in the sample. According to Jaffe and Trajtenberg (1996), the patent citations usually peak around four to five years after it is granted and taper off afterward. Combining this with the fact that only nine percent of the patents in the sample were granted after 2014, we make the argument that all patents have plenty of time to accrue citations beyond the general limitation of the citation data (only going back to 2001).

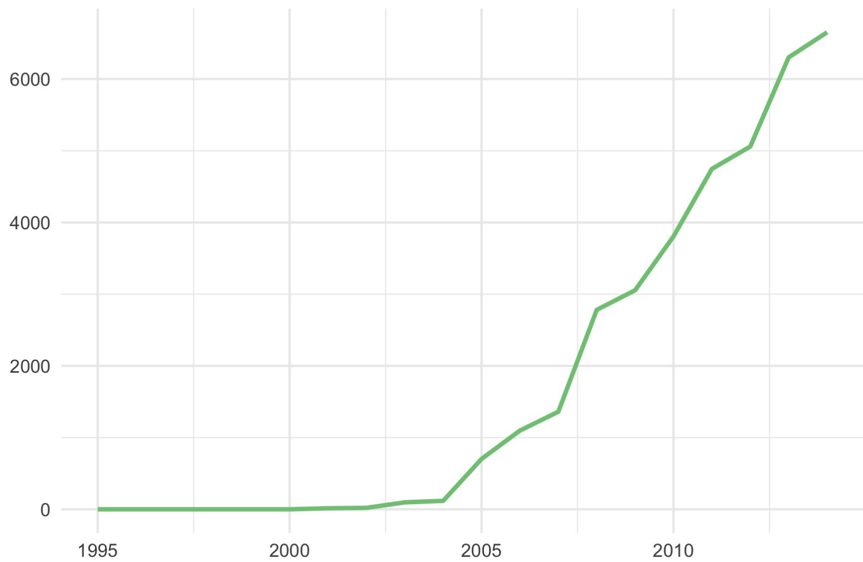

Figure 4.2: Annual Sum of Citations for Patents Applied for in Norway (1995-2014).

4.1.3 Company and Financial Data

An initial comparison of the USPTO and SNF samples showed some differences in how company names were spelled. This would effectively prevent analysis of company financial and board data for most firms if we had proceeded with a regular matching procedure. Instead, we loosened up the company name matching to allow for slight differences in spelling between the samples. To combine the now completed patent data with the company and financial data from SNF, we have applied the “fuzzyjoin” package in R to assist us in this process (Robinson et al., 2020). Fuzzyjoin allows the merging of data frames where merging column values are similar but not equal, using a max-difference to allow for some leeway in the spelling of the company names. This mostly captures differences in spelling between “AS,” “A.S.,” “A/S,” and other variation of the standard name for limited liability companies in Norway.

Our initial tests with the matching gave correct company matches up to a maximum distance of 0,2 before false positives started to appear. The matching procedure uses the Jaro Winkler similarity string metric to measure the edit distance between two sequences with a distance standardized between zero (exact match) and one (no similarities) (Robinson et al., 2020). To allow for large differences in spelling, we set the maximum distance to 0,2, manually checked the most considerable differences, and excluded incorrect matches. This matching procedure allowed us to increase the number of companies matched per year. There are certain instances of wrongly assigned company names in our sample, but we are satisfied with these numbers given the significant disparities between the original samples.

4.2 Defining the Variables

4.2.1 Dependent Variable

The primary dependent variable for our regression model will be the Patent Count in a given year for a given inventor. With the number of patents produced historically being used as a measure of innovation, we will also apply it in this research, in line with Moretti (2021), linking it to individual inventors. Because it is impossible for us as researchers to assess the size of an inventor’s contribution to a patent with many cited inventors, we employ the method Moretti (2021) used to divide the number of patents by the total number of participants on those patents. Patent Count summarizes the Patent Count an inventor is assigned for all patents they have contributed to in a given year. This effectively creates the inventor-year data where we have the total Patent Count for all inventors for all years they were active in the sample. This variable will allow us to capture the innovative quantity of the inventor without providing details on the quality of the patent.

$$\text{Patent Count}_i = \frac{\text{Total number of patents participated on in year } i}{\text{Total number of participants on these patents in year } i}, \quad \text{where } 1995 \leq i \leq 2014 \tag{4.1}$$

A secondary dependent variable is needed to capture the quality of patents for each inventor. In line with Moretti (2021), we define Citation-Weighted Patent Count (CWPC) as the Patent Fraction an inventor had for a patent times the subsequent number of citations that the patent received, summarized each year. This variable would capture the quality of the patents, thus deepening the analysis.

$$CWPC = Patent\,Fraction \times Citations\,Received \tag{4.2}$$

4.2.2 Independent Variables

The model includes three main independent variables: “Listed,” “Female,” and “Post.” These three variables are all binary (dummy) variables, meaning they either take a value of zero or one. First, the treatment variable “Listed” signifies whether the inventor works for a publicly listed company (one) or not (zero), as detailed in section 3.7.2. The gender variable “Female," turns one if the inventor is a woman and zero if he is not. Lastly, the time variable “Post,” indicates whether the observation occurred before (zero) or after (one) the event date. Using binary variables as the main independent variables quantifies these variables’ impact in a way that is simple to interpret.

4.2.3 Control Variables

We employ the use of several financial and company-specific factors that serve as control variables. This will help to reduce bias in the model and single out the effect of the actual variables the models are designed to test. Controlling for observable factors such as firm size (total assets), revenues, investments in R&D, chief executive officer (CEO) gender, CEO pay, board composition (number of members, as well as the gender of the chairman) and pay among others will likely provide a clearer view of factors relating to the research question.

Furthermore, we will apply a logarithmic transformation to financial control variables to achieve interpretable regression results and avoid much impact on other variables. This will create a logarithmic-logarithmic (log-log) relationship between the y-variable and the chosen x-variables. This was chosen as an interpretation of raw financial data on patenting productivity was futile, as many of the firms in the sample had large revenues and assets surpassing billions of kroner. The resulting log-log relationship provides more easily interpretable coefficients for these controls. The intuitive interpretation for the slope (beta) of log(revenue) is if revenue changes by one percent, then Patent Count changes on average one percent, given that other explanatory variables remain constant (Sucarrat, 2017).

4.3 Data Screening

4.3.1 Missing Values

The subject of "not available" (NA) or wrong values for the gender variable for certain individuals was identified as an issue with the patent data. To resolve this issue, we manually went through the 6,906 unique inventors in the sample to make sure they were given the correct gender. For certain individuals, their original gender was classified wrongly. Based on their names (mostly Norwegian) we attributed to them the right gender. The method is imperfect, but it serves to remove obvious mistakes in the data, namely where males have been ascribed the value of a female, wrongly inflating the number of females in the sample.

The interpolation process poses further complications to the data. Firstly, we need to address the issue of inventor gender in the interpolated year, which is complicated by the option to legally change one's gender in Norway. To accommodate this possibility, we assume that in the interpolated year, the inventor maintains the same biological sex as observed in the subsequent observation. Secondly, we must address the issue of the organization the inventor works for in the interpolated year. Suppose the inventor in year t+1 has produced a patent for firm x. In that case, we assume the inventor works for the same company in year t. The logic, therefore, suggests that we assign the following year's organization to the interpolated year for all individual investors.

Some inventors have produced multiple patents in a year for multiple companies or by themselves. To create the inventor-year observations, we need only one observation per inventor per year. To solve this issue, we add up the total patent fraction per inventor per year and select the other values based on the most frequent values for the inventor. For example, if the inventor worked for Norsk Hydro ASA for two patents in one year and filed one patent for another company in the same year, the inventor would be given the organization Norsk Hydro ASA. This simplification causes some data loss where inventors are part of multiple patents in a year filed by various companies. Because most inventors do not file multiple patents with multiple different companies each year, we believe the simplification is justified. Lastly, the dataset itself is inherently limited, given the nature of Oslo Børs. While historical information on the number of listed firms during the observed period is limited, the exchange accommodated between 150 and 214 stocks between 1994 and 2014, providing context for its scale. Consequently, the size of the treatment group is significantly constrained. There is very little we can do to address this limitation; hence one should be cautious in making conclusive assumptions based on the regression results alone.

4.3.2 Outliers

The financial data has been observed to contain significant outliers. These outliers, extremely small or large firms compared to the median, might impact the regression results, skewing the resulting regression line. Because of this, we winsorize the data. Winsorizing the data acts similarly to "trimming" the data for outliers with one clear exception: winsorizing implies changing all variable values above a chosen percentile to the percentile level, while "trimming" means removing all the outside observations. We ran a test whereby we winsorized at the 5% level (2,5% at both ends) across several financial, company, and patent variables, the result was a significant improvement in the quality of our analysis. We specifically chose 5%, as the dataset was subject to a number of significant outliers.

4.3.3 Normality

The normality assumption states that the residuals (the differences between observed and predicted values) should follow a normal distribution (the data is symmetrical around the mean and follows a bell shaped curve) (Chen, 2023). This assumption ensures reliable hypothesis testing, confidence intervals, and parameter estimates by allowing us to use critical values from a normal distribution (Rohrer, 2022b, p. 30). Studying the histograms and scatterplots of the main regression model residuals in figures B.1, B.2, B.3, and B.4 further increases our confidence in the normality of the sample.

4.3.4 Multicollinearity

Multicollinearity in a regression model is a high correlation between two or more independent variables (Hayes & Scott, 2023). When using a panel data sample following inventors over time, some factors regarding each inventor do not change. This fact is important to keep in mind. We, therefore perform a variance inflation factor (VIF) test and check the correlation table of the main independent variables. Additionally, by using inventor fixed effects and year fixed effects we intend to reduce the potential impact of multicollinearity by controlling for unobserved individual-specific and time-specific factors.

The VIF is a measurement of the amount of multicollinearity in a model (Potters, 2023). As such, it will help us identify whether any independent variables are highly correlated by displaying how much a variable contributes to the standard error in the regression. We calculate the VIF for each variable, allowing us to detect when significant multicollinearity between variables exists, as the VIF will be large for the variables involved (Potters, 2023).

$$VIF_i = \frac{1}{1 - R_i^2} \tag{4.3}$$

According to Potters (2023), the following threshold values for the VIF apply:

- $VIF = 1 \implies$ Variables are not correlated.
- $1 < VIF < 5 \implies$ Variables are moderately correlated.
- $VIF > 5 \implies$ Variables are highly correlated.

Table 4.2: Variance inflation factor results before removing variables.

Variable	VIF
Female	1.02
Post	1.20
Listed	1.57
log(Revenue)	1.55
log(Total Assets)	21.65
log(Equity)	20.76
Female Board Percent	1.20
log(R&D)	1.14
log(CEO Pay)	1.56
log(Board Pay)	1.45
CEO Gender	1.10
log(Employees)	1.69

From table 4.2 we see that log(Total Assets) and log(Equity) have high VIF values. These variables are intuitively correlated, so we will remove one of them from the models. We decide to remove log(Equity) form the models as we believe both control for firm size, but log(Total Assets) provides a more accurate representation of actual firm size.

Table 4.3: Variance inflation factor results after removing variables.

Variable	VIF
Female	1.02
Post	1.18
Listed	1.57
log(Revenue)	1.58
log(Total Assets)	1.86
Female Board Percent	1.19
log(R&D)	1.12
log(CEO Pay)	1.61
log(Board Pay)	1.46
CEO Gender	1.10
log(Employees)	1.78

Following the removal of log(Equity), no variables have significantly high multicollinearity (VIF > 5 (Potters, 2023)). Regardless, inspecting the correlation table B.1 reveals that several variables are correlated. These variables relate to company characteristics (Revenue, Total Assets, CEO pay, Board pay, Listed, R&D, and Employees). We decide to keep the variables in the models despite this correlation. This decision is motivated by the results of the VIF analysis and subsequent low degrees of multicollinearity, coupled with the fact that these are all control variables that will not be interpreted in the models.

4.4 Summary Statistics

Table 4.4: Summary statistics of inventors and patents.

	Number of unique inventors	Number of patents on which these inventors participated	Ratio
All inventors	6,906	5,218	0.76
Females	560	601	1.07
Self-employed	61	33	0.54
Listed firms	1,206	797	0.66
Unlisted firms	5,947	4,439	0.75

The sum of patents produced by self-employed inventors, and employees of listed, and unlisted firms are larger than the total sum of patents produced by all inventors because some patents are a product of collaboration between multiple firms. This is only a small number of patents, however, 49 patents in total.

Table 4.5: Annual statistics of inventors and patents.

	Mean	Median	Min	Max	SE
Patents Applied for	262	251	140	416	17
Count of Unique Inventors	616	615	309	1,020	44
Count of Unique Female Inventors	43	36	12	112	6

Before exploring the regression results, studying inventors' summary statistics already provides some insights into the data. First, the total number of unique female inventors per year increased by 600% over the twenty years, from 12 in 1995 to 83 in 2014. Total inventors increased by 230% over the same period from 310 in 1995 to 931 inventors in 2014.

5 Analysis and Results

This section will present and discuss results and regression tables from the analysis conducted according to Chapter 3. First, Section 5.1 presents and discusses results from the three main regression tables. Next, Section 5.2 deepens analysis by conducting several robustness checks and changes in assumptions related to the observed period, interpolation period, and observed inventors. Finally, Section 5.3 discusses important limitations of the results and interpretations.

5.1 Panel Data Regression

This section presents our regression results. The results include three main tables. All models include time (year)-fixed effects and entity (inventor)-fixed effects. Furthermore, all models are calculated with and without control variables linked to specific firm characteristics. Table 5.1 presents individual independent variable models to establish a baseline effect on inventor productivity. Next, Table 5.2 expands this to include an interaction term Post $\times$ Listed for a DiD interpretation. Table 5.3 includes all independent variables and all interaction terms between these.

Table 5.1: Individual dependent variable models and without female models. PC and CWPC.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	-0.039	0.016	0.015	0.195
	(-0.463)	(0.103)	(0.122)	(0.708)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	12,328	6,876	12,328	6,876
R^2	0.473	0.528	0.769	0.785

Clustered (Organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

The models in Table 5.1 examine how the logarithmic Patent Count and logarithmic CWPC of an inventor is impacted by employment by a listed firm. The year-fixed effects remove the Post variable due to high correlation. Similarly, the inventor-fixed effects remove the effect of the Female variable, as this controls for inventor-specific characteristics, such as gender.

Listed has a negative and non-significant impact on patent count, which turns positive and non-significant when adding control variables. The CWPC displays a positive and non-significant effect from the listed variable. The results in Table 5.1 indicate that the employer firm, publicly listed or not, by itself, does not have a significant difference from zero correlation with the inventor's patent quantity or quality. To see if this changes based on which point in time the inventor is actively researching and producing patents, we will expand the models to include an interaction term between Post and Listed.

Table 5.2: Post:Listed. With and without controls. PC and CWPC.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	-0.030	0.042	0.124	0.144
	(-0.266)	(0.195)	(1.041)	(0.451)
Post × *Listed*	-0.017	-0.051	-0.222	0.102
	(-0.119)	(-0.213)	(-1.224)	(0.351)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	12,328	6,876	12,328	6,876
R^2	0.473	0.528	0.769	0.785

Clustered (Organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5.2 presents the impact of the Listed variable and the interaction term between the Post and Listed variables. Again, Listed and the interaction term lack significant results for any of the model specifications. Although insignificant, the addition of the Post × Listed variable leaves us with similar coefficients for the Listed variable. Furthermore, the Post × Listed variable displays negative coefficients for all model specifications except the CWPC when adding control variables.

The analysis in Table 5.2 expands on the findings from Table 5.1 and reveals that neither the type of firm the inventor works at (publicly listed or private) nor the difference in difference estimator for Listed company inventors after the event date exhibit a statistically significant relationship with the dependent variable. This implies that, based on the data and models, we have no evidence to reject the null hypothesis of no relationship between Patent Count, CWPC, and Post × Listed. As these results are contradictory to the findings of Griffin et al. (2021), we expand the model further to look at potential inventor-gender-specific effects.

Table 5.3: All dependent variables with and without controls. PC and CWPC.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	-0.028	0.058	0.153	0.215
	(-0.231)	(0.262)	(1.281)	(0.666)
Female × *Post*	-0.097	-0.224	-0.358*	-0.388
	(-0.538)	(-0.801)	(-1.896)	(-1.131)
Female × *Listed*	-0.074	-0.361	-0.624*	-1.241
	(-0.294)	(-0.855)	(-1.922)	(-1.384)
Post × *Listed*	-0.023	-0.084	-0.228	0.092
	(-0.160)	(-0.331)	(-1.250)	(0.322)
Female × *Post* × *Listed*	0.135	0.494	0.141	0.526
	(0.522)	(1.301)	(0.309)	(0.482)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Observations	12,328	6,876	12,328	6,876
R^2	0.473	0.528	0.769	0.786

Clustered (Organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table 5.3 presents the complete regression model, including additional interaction terms between the female variable and all other independent variables. We observe no statistically significant results for the patent count regression whether we include control variables or not. This result makes empirical sense based on the graphs detailing the inventor productivity in both listed (Figure B.6) and unlisted firms (Figure B.7). We observe no spike in inventor productivity surrounding the event date, regardless of whether the inventor works for a listed or unlisted firm. This implies that the legislation did not affect the individual inventor's productivity, and that there is no correlation between the number of female board members and inventor productivity.

Interestingly, we observe a visually large increase in inventor productivity for female inventors, specifically working for listed firms three years following the event date, in 2007 (Figure B.6). Despite this observation, we find no statistically significant result for the Female × Post × Listed interaction term in Table 5.3 of the Patent Count regression. We believe the lack of significant results may be impacted by our assumptions; hence this will be explored further in Section 5.2.

The CWPC regression yields two statistically significant results. First, a female inventor observed after the event date has a 35.8% lower expected CWPC, significant at the 10% level. Additionally, we find that female inventors working at listed firms have a 62.4% lower expected CWPC, also significant at the 10% level. These effects lessen when we include control variables, and are no longer statistically significant on any level, despite still having a substantial negative effect. The R^2 of the Patent Count and CWPC regressions with the addition of control variables are 0.528 and 0.786, respectively, suggesting our models fit the data well.

The initial findings suggest that female inventors' innovative quality at large was adversely affected by the legislation. To accurately assess why such an effect would disappear we must turn to our control variables, as all regressions include entity and time fixed effects. R&D expenditures is a natural place to start, as it certainly affects the patent count and CWPC of a given firm. In this context, it could mean that female inventors tended to work at firms with lower R&D expenditures. Therefore, the quality of the patents produced was not worse due to the gender of the inventor, but rather the lack of spending on R&D, and subsequent resources provided by the respective firm. Historical gender prejudice could provide an explanation for this as science, technology, engineering, and math-related studies were particularly male-dominated throughout the 90s and 2000s in Norway (DBH, n.d.). Hence, prestigious Norwegian firms with heavy investments in R&D may have had a tendency to hire based on presumptions of what an inventor "was supposed to look like", resulting in female inventors struggling to land coveted positions in their field.

The number of employees could also affect the result, as larger firms may focus more on hiring based on socioeconomic backgrounds, race, or gender. This in turn, could mean that it is in fact larger firms that are adversely affected by the legislation, and not women, which would explain why the effect disappears with the addition of control variables. For example, we know larger firms are highly exposed to the public, and thus might have entered a period of transition following the legislation in which they were less effective, as they were required to re-adjust to expectations set by the public. The same logic could be applied to the revenue and CEO pay variables, as these are closely linked to the size of the firm.

The results detailed above differ considerably from those of Griffin et al. (2021). This is likely a product of the fundamentally different approaches to the topic and subsequent regressions performed. Whereas Griffin et al. (2021) focus on the effect of female board representation on firm-level innovation, we direct the focus to female board representation's effect on the individual inventor level. For this reason, the results cannot be compared directly and should rather be taken as complementary.

There are additionally notable differences pertaining to the technical side of the regressions. Firstly, we included a vast set of control variables we deemed important to reduce the chance of omitted variable bias, a measure Griffin et al. (2021) did not account for. Additionally, while Griffin et al. (2021) mainly focused on the post-legislation effects, our dataset and subsequent regressions encompass a greater period before the event date. This creates a more accurate baseline to review the differences in privately held and listed companies following the event date. Notably, Griffin et al. (2021)'s sample size is far smaller than ours, reaching a maximum of 526 observations. Notwithstanding the differences presented above, their models do not include the respective R^2-, or adjusted-R^2-values, which makes comparison of fit between the model(s) difficult. Ultimately, if we account for the lack of control variables, simpler form of regression, and considerably smaller sample analysed by Griffin et al. (2021), we fail to see why our results should be interpreted as less reliable, simply because they do not align with those of Griffin et al. (2021). This rings particularly true when accounting for the ambiguous nature of research done on the topic of diverse board representation and innovation. There is also the possibility that both analyses are correct, meaning that the treated firms see an improved innovative productivity and quality, even though the treated inventors themselves do not see an increase in productivity and/or quality.

The results from Table 5.3 provides the most complete foundation to discuss the hypotheses detailed previously in the thesis. We find no evidence suggesting that the legislation increased individual inventor productivity in listed firms, hence we cannot conclude on the validity of hypothesis 1. Despite finding no indication that expected inventor productivity increased following the legislation, the quality of innovations may have improved regardless. The CWPC results display similar tendencies as the patent count regression, however, as there is no indication that the legislation improved on the quality of innovation for inventors working at listed firms. We are therefore unable to conclude on the validity of hypothesis 2.

5.2 Robustness Checks

The regression results depend on several assumptions made regarding both the sample and variables. Because these assumptions may impact our results, we will now modify the main assumptions and re-estimate the models. Robustness checks are a way to see how the estimated models change when the central underlying assumptions change (Lu & White, 2014). The most important assumptions made to our sample are the choice of interpolation period, time of event date, period of analysis, and which inventors to include in the sample.

Table A.1 shows the interesting results of running the regression model on a reduced sample containing only inventors with more than one patent observation. By removing all inventors with only one observation from the sample, we cut the inventor pool down to $\approx$ 40% of its original size. The resulting sample is the remaining 40% most productive inventors. The females in this sample working in publicly listed firms after the event date has an expected 70.4% higher Patent Count (significant at the 5% level) than their male counterparts after controlling for firm characteristics and inventor fixed effects. Before including control variables, we observe negative correlations between Female $\times$ Post and Female $\times$ Listed, both significant at the 5% level. These findings all but disappear when controlling for firm characteristics. The above mentioned results indicate that the event impacted the most productive female inventors in a greater and more significant manner than the least productive female inventors.

As we shorten the timeframe by 3 years on both sides of the event date in table A.5, some of the previously observed effects prevail. We find that a female inventor filing a patent after the event date has a 45.9% lower expected CWPC, with a significance of 5%. Notably, when adding control variables, the severity of the effect is somewhat lessened and is no longer statistically significant. Interpolating at a two-year rather than a one-year basis (Table A.3) yields notable results in the patent count regression. Female inventors filing a patent in a listed firm post event date have a 50.5% higher expected patent count, with a significance of 10%. When we add our control variables, this effect increases to a 90.6% higher expected patent count, with significance increasing to 5%. This finding is in line with (Figure B.6) briefly discussed in the section above, as well as the robustness check ran on inventors with greater than one patent in the sample. These findings underline the crucial nature of the choice in interpolation period, as adjustments to this considerably affects the significance of our findings.

The two-year interpolation yields additional significant results in the CWPC regression. First, an inventor working at a listed firm has a 19.0% higher expected CWPC. Secondly, a female inventor working at a listed firm has a 65.1% lower expected CWPC. These results are significant at the 5% and 10% level, respectively, however, they turn statistically insignificant when adding the control variables. Aside from the Listed result, the Female × Listed result is in line with the findings of Table 5.3, further substantiating the results.

Why the effect on patent count strengthens with the additions of control variables is unclear. Our theory is that the two-year interpolation model results appear due to the low number of female inventors (Figure B.8). Since our sample contains few female inventors, the increased interpolation affects a substantially higher number of male inventors. In turn, this reduces the upward bias of multiple male inventors, whereas very few female inventors are affected. The effect increases in significance when adding control variables, because we remove the control variables' impact on the dependent variable, possibly because female inventors tend to work at firms with lower R&D expenditures, or at smaller firms. Hence, a purer estimate of the effect is achieved. This is reflected in the increased R^2. To further explore this effect we increased the interpolation to three years in A.4, by which all significant patent count results disappeared.

In extension of this, the transitionary period granted to listed firms may have resulted in a lagged effect on the observed increase in patent count of female inventors. This lagged effect may explain the substantial spike in female inventor productivity that was reduced to pre-event date levels within 2012. Conversely, we cannot rule out the possibility of increased female inventor productivity being a result of some other exogenous shock affecting publicly listed Norwegian firms from 2007 to 2012. The macroeconomic turmoil experienced during the Great Recession is a natural place to start. However, through which channel this positively affects female inventor productivity alone is unclear. Another explanation might be that the legislation increases female board representation, which indirectly leads to a temporary heightened focus on female inventors, which eventually falls back to normal levels a few years later.

5.3 Limitations

Firstly, although the event has been used as a natural experiment, the randomness of selection can still be questioned. Since the treatment group comprises solely of inventors working at listed firms that choose to remain public following the announcement of the legislation, we may incur a bias due to the very nature of companies that decide to go public. Public companies are commonly larger, more mature entities than private companies. Furthermore, the public companies of our treatment group may put less emphasis on R&D and long-term innovation due to the high, short-term pressure of being listed on a public exchange (Sappideen, 2011). In extension of this, the control group is not identical to the treatment group. Hence, although we mitigate this through fixed effects and control variables, we will never have statistically identical groups.

We do not, contrary to the practice of Griffin et al. (2021), employ the use of an instrument variable as our main dependent variable. We found no reason to employ the use of an Instrument Variable, as endogeneity concerns were low, despite our regression results differing significantly from theirs. In addition to the difference in methodology, sample size, control variables, and timeframe, their analysis of the Norwegian legislation change is brief, and only a fraction of the paper, whereas we have directed the entirety of our thesis' attention to the effects of the legislation change on individual inventors.

Determining the event date was a decision characterised by compromise, as the Post variable is inherently limited. As a reminder, the legislation first entered into effect January 1^{st}, 2004, however the transitionary period contingent on the ownership forms of the firms made it difficult to decide on an exact event date. One could argue we should have waited until after the transitionary period was over for all publicly listed firms (August 15^{th}, 2007) to get an accurate measure of innovation in a period when all publicly listed firms complied with the mandate. However, we want to measure the effect of the mandate itself on individual inventors, hence excluding the transitionary period from the post-variable would likely result in a bias, as the effects of the mandate may mistakenly be attributed to pre-event date factors. We controlled for this by changing the event date to August 15^{th}, 2007, and ran the regressions to ensure we checked for this. Speaking to the robustness of our results, the later event date yielded no significant results, allowing us to reallocate this model to the appendix.

Oslo Børs is a relatively small exchange, inherently limiting the size of the treatment group. As illustrated in Figure B.8, the number of female inventors working in listed firms is only a fraction compared to male inventors working in listed firms. Caution should be applied when interpreting all Female $\times$ Listed interaction coefficients. The number of male inventors working in listed firms appears to fluctuate significantly with the business cycles of the observed period (Table B.9), an element the female inventors working at listed firms appears less affected by. Furthermore, we may have an issue with classifying the inventors to their correct gender, as we had to manually do this by guessing whether a name belonged to a female or a male inventor. This proved easy for traditional western names, however, when faced with unfamiliar names, an educated guess was made.

The citation data had further limitations. We found no record of citations made on the patents before 2001, which, in our view, results from a combination of limitations in the dataset and our research methods. By measuring the patents at the filing date, we exclude any patents filed before 1995. Hence, a patent filed as early as 1995 would commonly take 18-24 months before being confirmed and granted (Patentstyret, 2016). Naturally, one can only cite a patent after it has been granted, and one is able to assess its purpose and benefit. This effect is substantiated by the findings of Jaffe and Trajtenberg (1996), who observe that, depending on the industry, the majority of citations are made within 5 – 7 years of the patent being granted. Additionally, the exponentiality in the citation data is affected by the total number of patents from our sample that are in circulation. An ever-increasing number of granted patents naturally leads to an increase in citations.

6 Conclusion

This thesis studies how gender diversity in the boardroom affects the innovative quantity and quality of the firm's individual inventors. Based on the findings and subsequent discussion, we conclude that individual inventors were largely unaffected by the legislation, suggesting there is no clear link between female board representation and innovative productivity at the inventor level. An avenue worth exploring further is the connection between the legislation and female inventor performance. We find there may be a relationship between the two, particularly for the most productive female inventors.

Similarly, we are left with inconclusive evidence regarding the impact on quality of innovation. We find no significant results suggesting that the quality of innovation increased in listed firms following the event date. Interestingly, there are indications that the legislation adversely affected the quality of patents produced by female inventors, however these findings turned insignificant in all instances when we included control variables. Notably, the citation data had significant limitations, hence we suggest that any further research done on CWPC be done with samples of greater completeness.

In short, despite the conclusive findings of Griffin et al. (2021), we find no evidence suggesting that the observed effect of female board representation trickled down to the innovative quantity or quality of the individual inventor.

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Appendices

A Regression tables

Table A.1: Main model only including inventors with >1 patent observation.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Variables				
Listed	-0.028	-0.028	0.153	0.217
	(-0.285)	(-0.164)	(1.579)	(0.923)
Female × *Post*	-0.097	-0.298	-0.358**	-0.433
	(-0.663)	(-1.343)	(-2.339)	(-1.632)
Female × *Listed*	-0.074	-0.550	-0.624**	-1.088*
	(-0.363)	(-1.385)	(-2.371)	(-1.660)
Post × *Listed*	-0.023	-0.098	-0.228	0.057
	(-0.198)	(-0.550)	(-1.542)	(0.256)
Female × *Post* × *Listed*	0.135	0.704**	0.141	0.461
	(0.644)	(2.139)	(0.381)	(0.542)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	8,104	5,049	8,104	5,049
R^2	0.383	0.451	0.683	0.712

Clustered (organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.2: Main regression table with all controls.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	-0.028	0.058	0.153	0.215
	(-0.231)	(0.262)	(1.281)	(0.666)
Female × Post	-0.097	-0.224	-0.358*	-0.388
	(-0.538)	(-0.801)	(-1.896)	(-1.131)
Female × Listed	-0.074	-0.361	-0.624*	-1.241
	(-0.294)	(-0.855)	(-1.922)	(-1.384)
Post × Listed	-0.023	-0.084	-0.228	0.092
	(-0.160)	(-0.331)	(-1.250)	(0.322)
Female × Post × Listed	0.135	0.494	0.141	0.526
	(0.522)	(1.301)	(0.309)	(0.482)
log(Revenue)		0.001		0.009
		(0.242)		(1.211)
log(Total assets)		-0.088		-0.065
		(-1.335)		(-0.599)
Female board percent		-0.074		-0.613
		(-0.276)		(-1.133)
log(R&D)		0.004		0.007
		(0.836)		(0.736)
log(CEO pay)		-0.001		0.006
		(-0.253)		(0.624)
log(Board pay)		0.004		0.002
		(0.789)		(0.203)
log(Num. employees)		0.000		0.000
		(-0.051)		(0.000)
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	12,328	6,876	12,328	6,876
R^2	0.473	0.528	0.769	0.786

Clustered (organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.3: Two-year interpolation. All dependent variables with and without controls. PC and CWPC.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	0.021	0.051	0.190**	0.251
	(0.158)	(0.213)	(2.028)	(0.826)
Female × *Post*	-0.119	-0.266	-0.392	-0.485
	(-0.592)	(-1.147)	(-1.638)	(-1.301)
Female × *Listed*	-0.326	-0.684	-0.651*	-1.242
	(-1.266)	(-1.565)	(-1.689)	(-1.265)
Post × *Listed*	0.060	0.066	-0.169	0.115
	(0.345)	(0.285)	(-1.054)	(0.446)
Female × *Post* × *Listed*	0.505*	0.906**	0.306	0.815
	(1.650)	(2.511)	(0.684)	(0.761)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	13,338	7,426	13,338	7,426
R^2	0.424	0.480	0.717	0.741

Clustered (Organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.4: Three-year interpolation. All dependent variables with and without controls. PC and CWPC.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	0.040	-0.109	0.160*	0.087
	(0.350)	(-0.533)	(1.888)	(0.285)
Female × *Post*	-0.010	-0.110	-0.440**	-0.448
	(-0.052)	(-0.519)	(-2.213)	(-1.409)
Female × *Listed*	-0.116	-0.189	-0.681**	-1.095
	(-0.356)	(-0.369)	(-2.058)	(-1.581)
Post × *Listed*	0.128	0.200	-0.159	0.006
	(0.901)	(0.810)	(-0.996)	(0.021)
Female × *Post* × *Listed*	0.288	0.443	0.309	0.694
	(0.860)	(1.057)	(0.751)	(1.028)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	14,322	7,972	14,322	7,972
R^2	0.421	0.487	0.683	0.708

Clustered (organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.5: 1997-2011. All dependent variables with and without controls.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	-0.081	0.019	0.035	0.228
	(-0.542)	(0.066)	(0.272)	(0.706)
Female × *Post*	-0.130	-0.297	-0.459**	-0.531
	(-0.633)	(-0.869)	(-2.155)	(-1.479)
Female × *Listed*	-0.033	-0.063	-0.444	-0.662
	(-0.109)	(-0.107)	(-1.180)	(-0.588)
Post × *Listed*	-0.038	-0.233	-0.284	-0.045
	(-0.231)	(-0.682)	(-1.530)	(-0.156)
Female × *Post* × *Listed*	0.174	0.522	0.317	0.494
	(0.603)	(0.972)	(0.644)	(0.444)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	8,878	4,419	8,878	4,419
R^2	0.471	0.547	0.760	0.802

Clustered (organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

Table A.6: Main model including pre 2004 and post 15. august 2007 dummy variables.

Dependent Variables:	log(Patent Count)		log(Citation-Weighted PC)	
Model:	(1)	(2)	(3)	(4)
Listed	-0.011	-0.083	-0.067	0.241
	(-0.119)	(-0.443)	(-0.503)	(0.801)
Female × *Post*	-0.136	-0.190	-0.149	-0.667
	(-0.845)	(-0.882)	(-0.268)	(-0.932)
Female × *Pre*	-0.169	-0.059	0.261	0.161
	(-1.263)	(-0.199)	(1.275)	(0.335)
Female × *Listed*	0.082	0.353	-0.217	-0.510
	(0.523)	(1.324)	(-0.555)	(-0.735)
Post × *Listed*	-0.136	-0.081	0.087	-0.170
	(-1.287)	(-0.396)	(0.290)	(-0.329)
Pre × *Listed*	0.025	0.062	0.213*	-0.118
	(0.197)	(0.289)	(1.684)	(-0.589)
Female × *Post* × *Listed*	0.375	-0.023	-1.247	-0.683
	(0.832)	(-0.069)	(-1.150)	(-0.596)
Female × *Pre* × *Listed*	-0.134	-0.586	-0.474	-0.783
	(-0.695)	(-1.536)	(-1.462)	(-0.743)
Controls:	No	Yes	No	Yes
Clustered SE:	Yes	Yes	Yes	Yes
Fixed-effects				
Inventor	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	12,328	6,876	12,328	6,876
R^2	0.729	0.769	0.811	0.828

Clustered (organization) co-variance matrix, t-stats in parentheses
*Signif. Codes: ***: 0.01, **: 0.05, *: 0.1*

B Visual Analysis of Residuals and Data

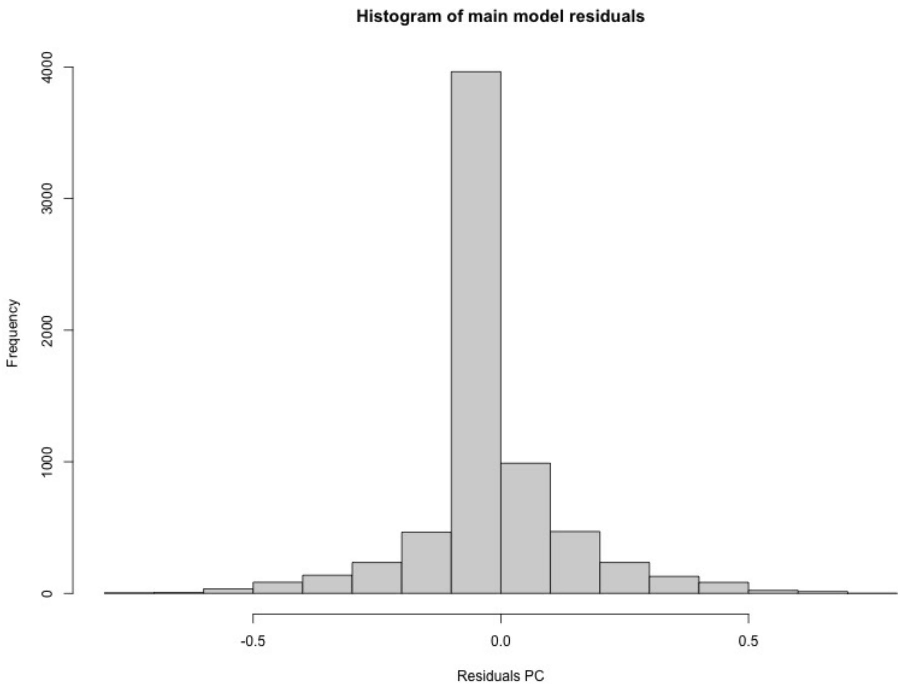

Figure B.1: Histogram of PC residuals

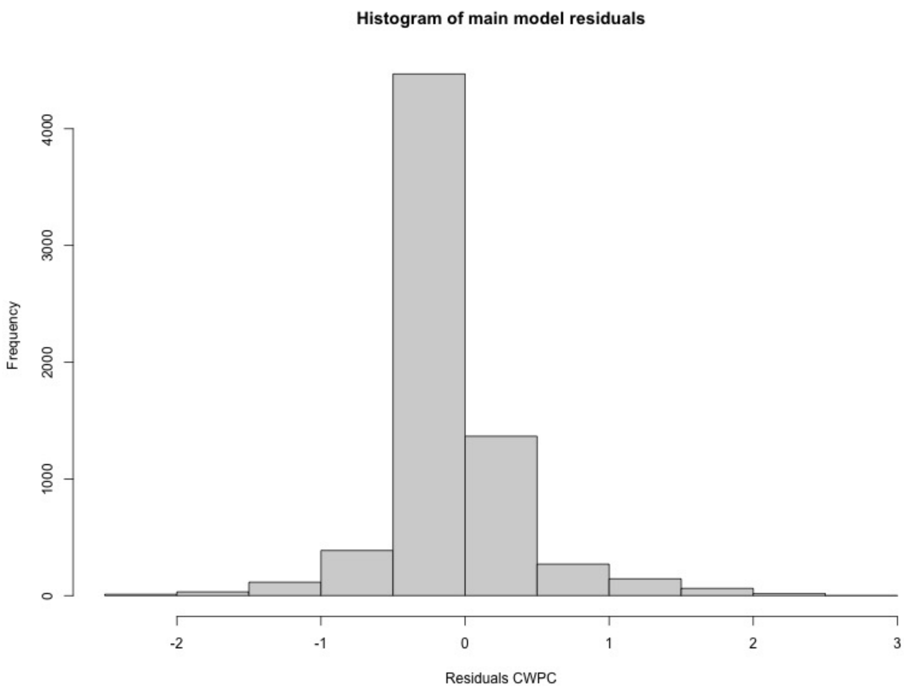

Figure B.2: Histogram of CWPC residuals

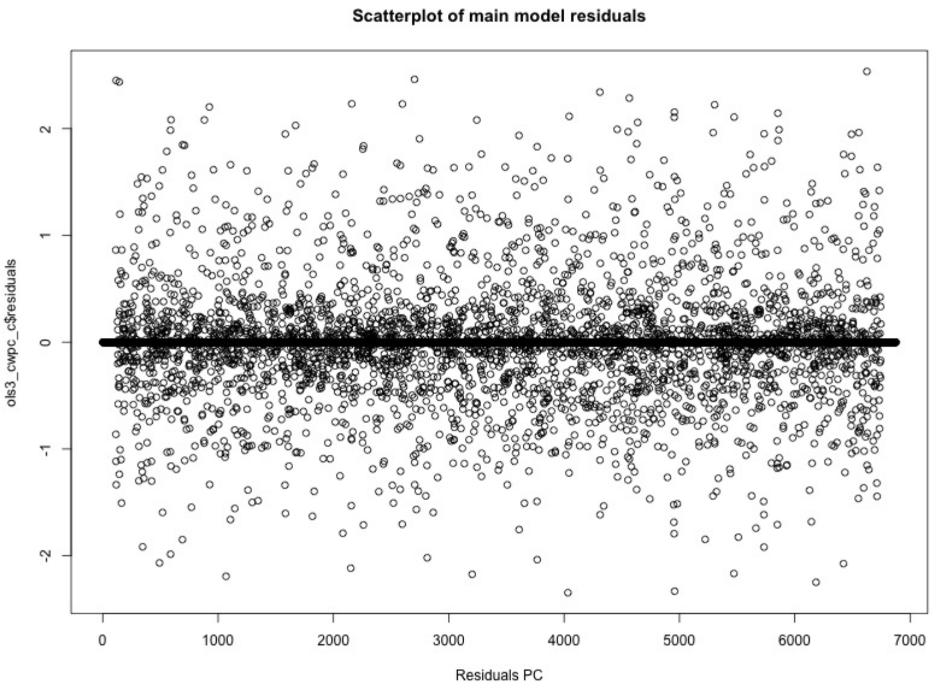

Figure B.3: Scatterplot of PC residuals

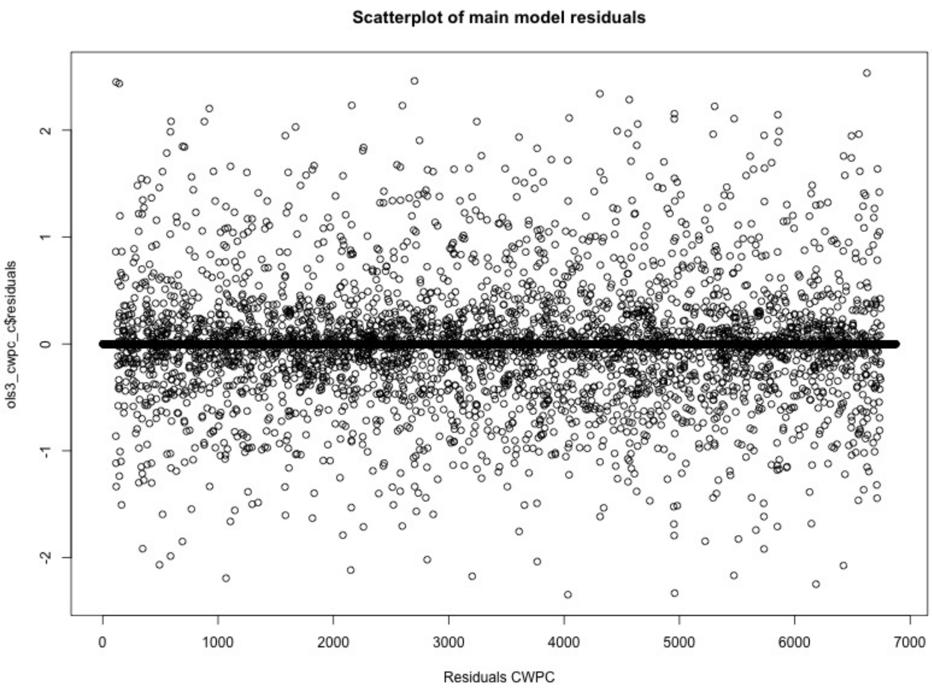

Figure B.4: Scatterplot of CWPC residuals

Figure B.5: Percent patents with atleast one female participant by year

The number of patents with more than one female participant increases significantly in the year following the event date. This is a lasting effect which only increases the further we move from the event date.

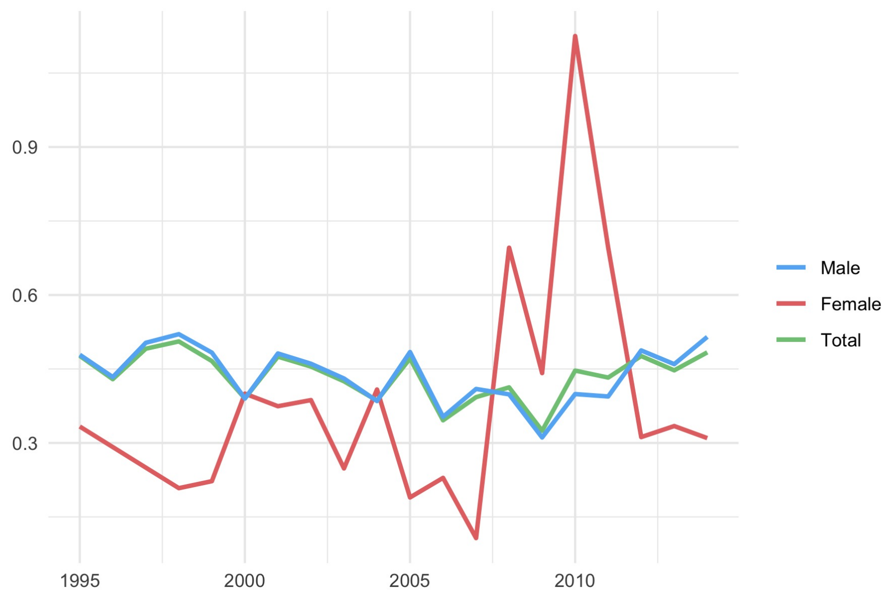

Figure B.6: Inventor productivity listed firms

Female inventor productivity in listed firms spikes disproportionally to male inventor productivity in the period of 2007 – 2012. The effect then disappears entirely.

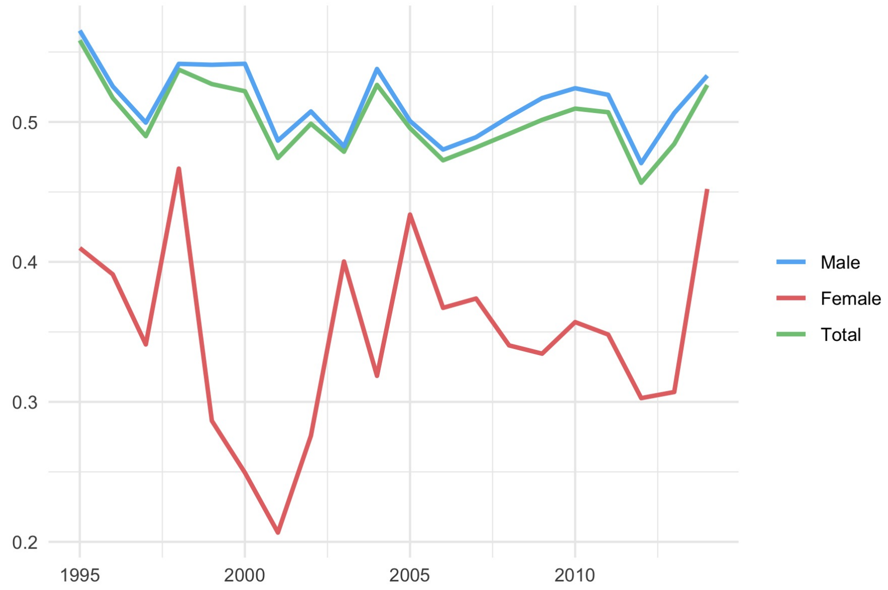

Figure B.7: Inventor productivity unlisted firms

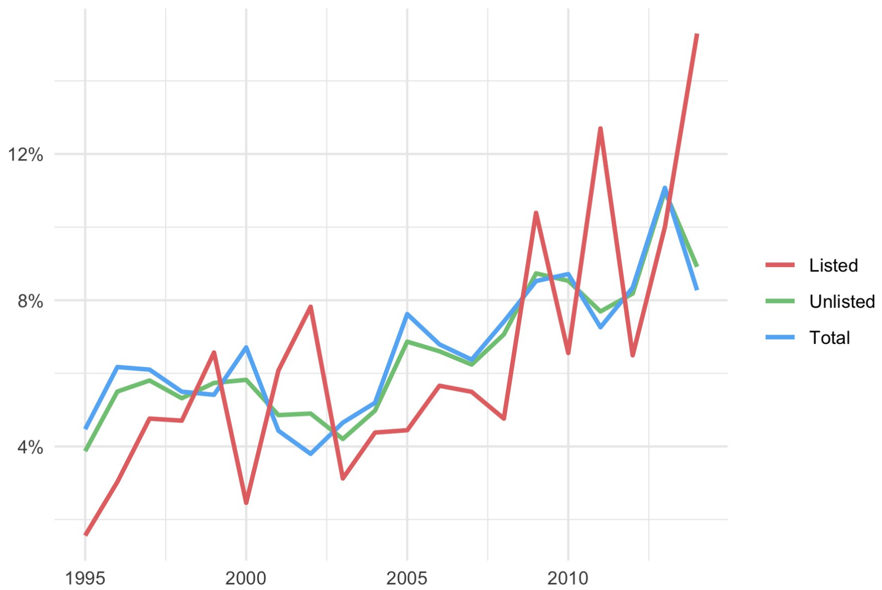

Figure B.8: Percent female to all inventors

The percent of females to all inventors is increasing, yet highly volatile in listed firms. The volatile effect is not observed in the unlisted firms.

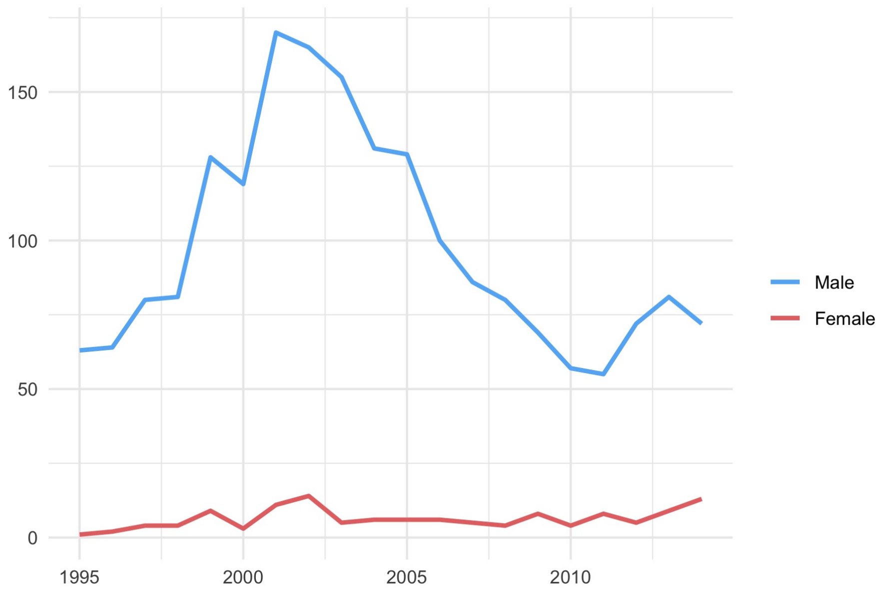

Figure B.9: Number of unique inventors listed firms by year

Table B.1: Correlation table of independent variables.

	Ffemale	Post	Listed	Revenue	Total assets	Female board percent	rnd	ceopay	Board pay	CEO gender	Num. Employees
Female	1,00	0,05	0,01	0,00	0,00	0,11	- 0,03	- 0,02	0,02	- 0,08	0,05
Post	0,05	1,00	- 0,28	0,03	- 0,02	0,02	0,16	0,09	- 0,18	- 0,00	- 0,13
Listed	0,01	- 0,28	1,00	0,18	0,27	0,21	- 0,09	0,25	0,61	0,15	0,35
Revenue	0,00	0,03	0,18	1,00	0,93	0,14	0,51	0,05	0,23	0,06	0,31
Total assets	0,00	- 0,02	0,27	0,93	1,00	0,17	0,50	0,10	0,35	0,07	0,37
Female board percent	0,11	0,02	0,21	0,14	0,17	1,00	- 0,02	0,18	0,19	- 0,18	0,21
R&D	- 0,03	0,16	- 0,09	0,51	0,50	- 0,02	1,00	- 0,03	- 0,08	0,04	- 0,05
CEO pay	- 0,02	0,09	0,25	0,05	0,10	0,18	- 0,03	1,00	0,41	0,05	0,29
Board pay	0,02	- 0,18	0,61	0,23	0,35	0,19	- 0,08	0,41	1,00	0,11	0,54
CEO gender	- 0,08	- 0,00	0,15	0,06	0,07	- 0,18	0,04	0,05	0,11	1,00	0,07
Employees	0,05	- 0,13	0,35	0,31	0,37	0,21	- 0,05	0,29	0,54	0,07	1,00