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Navigating Technological Disruptions: The Impact of Board Diversity on Firm Performance

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Abstract

This paper explores the impact of board diversity on firm performance in times of technological disruption. Leveraging data on board characteristics, firm performance, and patents from 2011 to 2019, this study constructs a technological disruption dummy variable based on patent activity within industries. The study employs a fixed effects regression model to analyse how variations in board diversity, including age, gender, nationality, and tenure, influence firm performance metrics such as return on assets and return on equity. This paper identified a significant negative impact of board diversity on firm performance during technological disruptions, with a 10% significance level for return on assets and a 5% level for return on equity. However, the results vary based on the type of diversity, the definition of technological disruption, and the firm performance measure used. This research contributes to the understanding of how corporate governance can adapt to and potentially benefit from rapid technological changes affecting their industries.

Keywords: Board Diversity, Technological Disruptions, Firm Performance, Corporate Governance, Innovation.

JEL Classification: G34, O32, J2

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1. Introduction

In the continuously evolving landscape of the 21st century, numerous technological disruptions have reshaped entire industries. Artificial Intelligence (AI) and Machine Learning (ML) have revolutionized sectors from finance to healthcare, offering unprecedented capabilities in data analysis and decision-making. Similarly, cloud computing has solved traditional IT infrastructure barriers, enabling businesses of all sizes to scale their operations. Concurrently, the automotive industry is undergoing a significant transformation with the introduction of electric vehicles. These are only a few of the numerous technological disruptions that have had a big impact on businesses.

To successfully navigate technological disruptions, firms need a competent board of directors to advise and monitor the workforce. Extensive research has already been conducted on the characteristics of a strong board of directors. An important characteristic of a corporate board could be the magnitude of diversity among several factors such as gender, age and nationality. A diverse board could have a broader perspective on certain challenges which could positively impact firm outcomes. Bernile et al. (2018) find that boards with greater diversity are better at managing risk. Fernández and Gaite (2020), and Jonson et al. (2019) show the benefits of age diversity in a corporate board. Brahma et al. (2020) find that board gender diversity positively impacts firm performance in the UK.

While it is clear that board diversity impacts firm outcomes, its specific impact on firm performance during technological disruption has been overlooked. Times of technological disruptions are pivotal as they introduce substantial industry shocks, which may necessitate diverse board member characteristics to effectively manage these changes. Building on this premise, this paper aims to explore the broader role of board diversity during such disruptive periods. By examining how diverse attributes of board members affect firm performance, specifically in terms of Return on Assets (ROA) and Return on Equity (ROE), this research seeks to provide new insights into the critical role a varied board plays in navigating through times of rapid technological change. This leads to the following research question:

'How does board diversity impact firm performance during times of technological disruption?'

Understanding the impact of board diversity during times of technological disruption has significant implications on corporate governance, policy-making and strategic business management. Identifying whether there exists a correlation between these 2 variables in this context, can help in the selection and assembly of corporate boards to maintain a competitive advantage in the modern business environment.

To analyse the impact of board diversity on firm performance amid technological disruptions, this paper will leverage patent data from the USPTO database. By pinpointing spikes in patent filings within specific industries and correlating these with recognized disruptive events, periods of technological disruptions will be identified. Furthermore, this paper will gather information on board composition, focusing on the age and gender of directors. Utilizing these variables, a board diversity index will be constructed. The performance metrics return on assets and return on equity will be collected. Furthermore, this study will include control variables to consider diverse firm-level characteristics and environmental factors. Specifically, firm size will be assessed using market capitalization data, financial health will be evaluated using the debt-to-equity ratio, investment in innovation will be measured by research and development expenditure as a percentage of sale, and firm age will be accounted for as the difference between the first year on Compustat and the observation year.

The study will utilize a fixed-effects panel data analysis to explore the dynamic relationship between board diversity and firm performance, specifically during the identified periods of technological disruption. Dependent variables in the regression model include return on assets and return on equity, serving as proxies for firm performance. Independent variables consist of the board diversity index, a dummy variable indicating technological disruption, the interaction between board diversity and technological disruption, and all control variables. Of particular interest is the interaction effect between board diversity and technological disruption, as it provides insights into the additional impact of board diversity on firm performance during technological disruptions.

The results from models 1-4 demonstrated that board diversity negatively impacts firm performance during technological disruptions, with this effect reaching statistical significance at the 5% level in model 2 and at the 10% level in models 1 and 3. Conversely, models 5-8, which applied a more extreme definition of technological disruptions, indicated a contrary effect, though these findings were not statistically significant. This implies that increased board diversity might negatively affect a firm's performance during periods of significant technological change.

The paper proceeds as follows: Section 2 reviews the relevant literature. Section 3 describes the data and methods used in our models. Section 4 presents the results of our models. Section 5 discusses these results. Section 6 gives the conclusion of our research.

2. Theoretical framework

This theoretical framework will delve into several key areas. First, it will define and discuss various key aspects of board diversity and firm performance, outlining previous literature on these topics and their relationship. Second, it will examine previous literature on technological disruptions and how it could alter this relationship. A thorough examination of previous findings on these topics will assist in developing a hypothesis for the research question of this paper.

2.1 Board diversity

Board diversity refers to the presence and representation of varied demographic backgrounds and experiences within a company's board of directors. Firms with a diverse board could benefit from having different perspectives on topics, wider access to resources and connections, motivation for employees that their minority status is not a hindrance, and in publics relations for the firm. On the other hand, board diversity could also cause conflict, lack of cooperation, and insufficient communication, or a forced focus on board diversity could cause the selection of inadequate directors (Kent Baker & Anderson, 2010). In this paper, we explore four critical components of board diversity: diversity in age, gender, nationality, and board tenure.

Gardiner (2022) has examined 54 empirical papers from 1996 to 2022 finding that age diversity is positively correlated with corporate social responsibility (CSR) but is not a consistent predictor for other firm outcomes. This suggests a nuanced influence of age diversity. Backes-Gellner and Veen (2012) have also investigated age diversity and they found that increasing age diversity within a company's workforce has a positive effect on company productivity if a company engages in creative rather than routine tasks. This further highlights the importance of incorporating age diversity as a key component of board diversity, especially during periods of technological disruption when creative solutions are essential.

Boulouta (2012) found that board gender diversity positively impacts a firm's focus on CSR, based on a sample of 126 S&P 500 firms. Gul et al. (2011) showed that gender-diverse boards in U.S. companies enhance transparency and incorporate more firm-specific information into stock prices. Lenard et al. (2014) found that greater gender diversity on boards reduces stock market return variability. These findings provide strong evidence for the positive influence of gender diversity on firm outcomes, making it a valuable component to study in board diversity.

Regarding nationality diversity, Harjoto et al. (2019) have found that nationality diversity positively influences a firms' corporate social performance. Zaid et al. (2020) found a positive but weak relationship between nationality diversity in the board of directors and corporate sustainability performance. Kaczmarek and Nyuur (2021) demonstrated that nationality diversity impacts board commitment, measured by the number of board meetings and evaluations. These studies highlight the importance of nationality diversity in board operations, making it a key variable in this research.

Another widely studied topic is board tenure. Li and Wahid (2017) found that boards with higher tenure diversity exhibit better CEO performance-turnover, fewer accounting restatements, and less excess compensation, indicating more effective firm monitoring. Ji et al. (2021) reported that tenure diversity reduces stock return volatility, while Phuong et al. (2022) found it increases investment efficiency by reducing abnormal investments. These studies underscore the importance of board tenure diversity, validating its inclusion in this research.

In conclusion, the substantial evidence connecting board diversity to various firm outcomes supports the focus of this research on firm performance, especially in the context of technological disruptions. This approach highlights the importance of examining how diversified boards may influence outcomes during these transformative times. Previous literature has proven that each component of board diversity, including diversity in age, gender, nationality, and board tenure, is an important aspect to consider in our research as they might influence firm outcomes in our research context.

2.2 Firm performance

Firm performance measures a company's success using financial metrics like return on assets (ROA) and return on equity (ROE), as well as non-financial metrics such as market share and customer satisfaction. This study focuses on ROA and ROE due to their prevalence in research and data availability.

Research shows that corporate governance significantly impacts firm performance. Brown and Caylor (2004) found stronger governance leads to better performance and higher payouts. Bhagat and Bolton (2008) confirmed this, while Mashayekhi and Bazaz (2008) found board size negatively affects performance, but outside directors strengthen it. These studies suggest that board diversity could also be influential during technological disruptions.

CEO characteristics also impact firm performance. Bhagat et al. (2010) found that better-educated CEOs improve short-term performance. Peni (2012) showed that the presence of female CEOs positively impacts firm performance, whilst the candidate's experience and quality also has a positive effect. Bandiera et al. (2020) distinguished between "leader" and "manager" CEOs and found that firms which hire leaders perform better. Altogether, these studies show how leadership influences firm performance, strengthening the possibility of impact which board diversity could have.

2.3 Board diversity and firm performance

Additionally, quite some research has been done linking the 2 main topics of this paper, board diversity and firm performance. Bernile et al. (2018) show that firms with greater diversity are better at managing risk and stabilizing firm performance. Darmadi (2010) found that gender diversity negatively correlates with performance, nationality diversity has no impact, and younger board members positively relate to market performance. Brahma et al. (2020) found the opposite effects for gender diversity on firm performance. They specifically looked at FTSE 100 firms in the UK and found a positive significant relationship between gender diversity and firm performance. Fernández and Gaite (2020) found that age diversity positively impacts performance for both inside and outside directors, while nationality diversity benefits only inside directors. They found no impact of gender diversity. Ciavarella (2017) found no significant relationship between demographic diversity and performance across Europe, but firms with more female and foreign executive directors performed better. Cognitive diversity with longer tenure also improved performance. Khidmat et al. (2020) found that gender, education and nationality diversity have significant positive effect on firm performance. Age and director independence diversity seemed not to have a significant effect. Opposingly, Frijns et al. (2016) that cultural diversity in boards negatively affects firm performance measured by Tobin's Q and ROA.

All in all, a lot of studies have been done on the impact of board diversity on firm performance. The results are not all aligned. A lot of studies find a positive relationship between (certain components of) board diversity and firm performance, but Frijns et al. (2016) found the opposite. This shows that there is no clear answer to the significance and direction of this relationship, but that it is heavily dependent on the context. That makes the context of this paper so interesting as it looks specifically at firms in times of technological disruptions that may require distinctly different board qualities compared to those examined in prior studies.

2.4 Technological disruptions

Technological disruptions refer to significant innovations that fundamentally change the way of doing business in a specific industry. Khan (2020) studied food delivery innovations in the restaurant industry, showing how they transformed business models and skills required. Smith (2006) examined how computer game technologies disrupted the military simulation industry, providing affordable and versatile training solutions that reshaped competitive dynamics. Naylor (2017) discussed how AI, IoT, and Cloud Computing are disrupting the insurance industry by enhancing data analysis, customer service, risk assessment, and operational processes.

Hewlett et al. (2013) found that diversity enhances innovation, as diverse teams produce and develop more 'out-of-the-box' ideas. Rodríguez-Gulías et al. (2023) found that gender diverse top management teams positively impact firm innovation. Miller and Del Carmen Triana (2009) found that board racial and gender diversity positively impacts innovation and firm reputation, which in turn enhance firm performance. All these studies come to the same conclusion which is that a diverse set of views positively impacts innovation.

As mentioned previously, in a lot of cases, board diversity has been found to have an influence on firm performance. Technological disruptions require firms to adapt fast, which requires strong leadership to steer the company into the right direction. The role of the board is to advise and monitor the company's management, especially in these rapidly changing periods. As mentioned in the previous paragraph, a diverse team significantly enhances a firm's capacity to innovate, which is a skill that could be very important in disruptive periods. This makes it particularly interesting to investigate whether diverse boards impact not only general firm performance and innovation but also specifically whether a firm can benefit from a diverse board during times of technological disruptions.

2.5 Hypothesis

Looking at prior research we find that the impact of board diversity on firm performance heavily depends on the context. However, in most cases, board diversity seemed to have a positive effect on performance. Furthermore, board diversity seems to positively impact innovation as found by Miller and Del Carmen Triana (2009) and Rodríguez-Gulías et al. (2023). As technological disruptions are mostly driven by strong innovations in a certain industry, firms with high innovation capacities are likely better equipped to navigate such changes. Given the role of innovation in driving successful adaptation to technological disruptions, and the positive impact of board diversity on innovation, it is logical to propose that diverse boards may enhance firm performance particularly well during times of technological change. This leads us to the following hypothesis:

> ***H1**: Board diversity will have a positive impact on firm performance in times of technological disruptions.*

This hypothesis suggests that the different perspectives and experiences of a diverse board help a firm adjust its strategy and innovate, improving its performance during periods of technological disruption.

3. Data & Methodology

3.1 Data

3.1.1 Technological disruption dummy variable

To identify whether there was a technological disruption in a specific industry, patent data was collected from the USPTO database. Firstly, data was collected on all patents granted in the US, which year it was granted, and to which company it was granted to, between 2011 and 2019. This yielded 1,455,860 data points. Secondly, data was collected on the number of forward citations per patent from a different dataset in USPTO. Merging these two datasets resulted in no loss of patents. Thirdly, the *patent_weight* was calculated for each patent. This variable is specified as follows:

patent_weight = 1 + number of forward citations

This metric, *patent_weight*, reflects the significance of a patent which was granted in a specific year, considering the volume of forward citations, and provides a more nuanced measure than simply counting patents.   Next, each company in the patent dataset was categorized according to the Global Industry Classification Standard (GICS) using a Compustat industry dataset. The GICS is an industry taxonomy developed in 1999 by MSCI and Standard & Poor's (S&P) for use by the global financial community. Merging these 2 datasets yielded 938,231 left over patents. Following, the total *patent_weight* per industry per year was calculated. Finally, the dummy variable *technological_*disruption was constructed. For each industry, the mean and standard deviation of *patent_weight* was calculated for the data ranging from 2011 to 2019. Then, the dummy variable was constructed, for each year and each industry, as follows:

$$technological\_disruption_{i,t} = \begin{cases} 1, & patent\_weight_{i,t} > mean_i + \ standard\ deviation_i \\ & 0, else \end{cases}$$

where *i* represents the industry of the variable and *t* the year. This implies that the dummy variable is equal to 1 if the *patent_weight* for a specific industry in a specific year is bigger than the mean + standard deviation of the *patent_weight* for that industry. Additionally, this paper uses a more extreme definition of a technological disruption. The dummy variable is then constructed as follows:

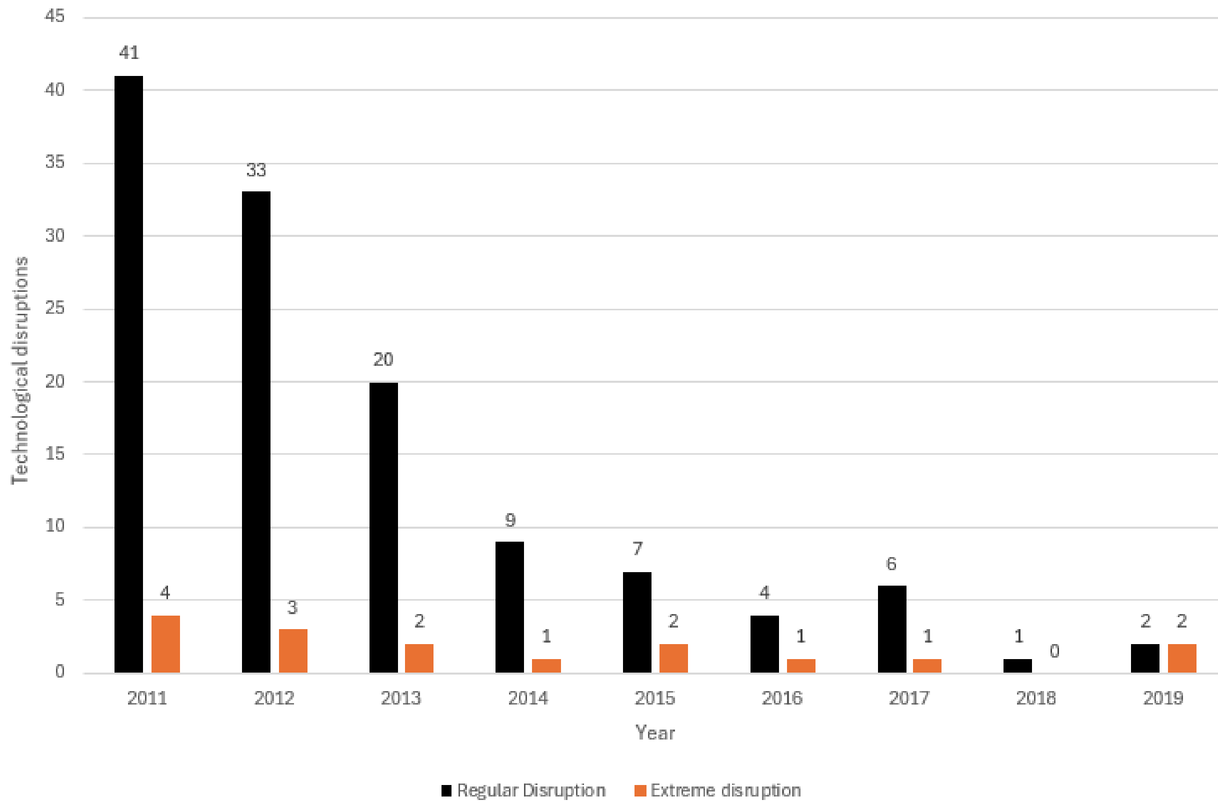
$$extr\_technological\_disruption_{i,t} = \begin{cases} 1, & patent\_weight_{i,t} > mean_i + \ 2 * standard\ deviation_i \\ & 0, else \end{cases}$$

where *i* represents the industry of the variable and *t* the year. This implies that the dummy variable is equal to 1 if the *patent_weight* for a specific industry in a specific year is bigger than the mean + 2* standard deviation of the *patent_weight* for that industry. This resulted in a dataset for 82 GICS industries, spanning from 2011-2019, detailing the occurrence of technological disruptions. For additional robustness, this thesis also employs a technological disruption dummy variable based on the median of *patent_weight* within each industry, rather than the mean.

Figure 1 represents the annual count of industries experiencing technological disruptions from 2011 to 2019. For the regular disruption definition, there is a significant peak in 2011 where 41 out of 82 industries undergo a technological disruption. This peak may be attributed to several technological advancements which impacted multiple industries simultaneously. Following 2011, there is a noticeable decline in the number of industries experiencing technological disruptions, reaching a low in 2018 with only 1 industry. For the extreme disruption definition, we see a peak as well in 2011. However, the numbers are much closer to each other with a peak of 4 in 2011 and a, similarly to the regular definition, a low in 2018 of 0.

Figure 1

Number of industries with a technological disruption 2011 - 2019



Note: total number of industries is 82 for each year

3.1.2 Board diversity index

To quantify the diversity of a board we construct a board diversity index, similarly as Bernile et al. (2018). To construct this index, data was collected from the BoardEx – Organization Summary - Analytics database on the proportion of females on the board *(female_ratio),* the standard deviation of the ages of all directors on the board *(sd_age)*, the standard deviation of board tenure of all directors *(sd_timeboard)*, and the proportion of directors from a different country *(int_ratio)*. These four components where then standardized to calculate the board diversity index as follows:

$$board\_diversity\_index_{i,t} = \frac{std\_female\_ratio_{i,t} \ + \ std\_age_{i,t} \ + std\_timeboard_{i,t} + std\_int\_ratio_{i,t}}{4}$$

where *i* represents the company of the variable and *t* the respective year. As can be seen in the previous chapter, a lot of researchers mainly focused on the components age and gender for board diversity. That is why, for robustness, an alternative board diversity index is constructed which looks as follows:

$$alt\_board\_diversity\_index_{i,t} = \frac{std\_female\_ratio_{i,t} \ + \ std\_age_{i,t}}{2}$$

where *i* represents the company of the variable and *t* the respective year. This alternative index only accounts for gender and age diversity.

Merging this dataset with the technological disruption dummy dataset yields 33,876 observations showing for each company and year the board diversity index and whether there was a technological disruption in the industry of that company for that year.

d*iv_tech* is the interaction variable between the dummy variable *technological_disruption* and the *board_diversity_index*. The coefficient of this variable will explain what the impact is of a diverse board on firm performance given that we are in a time of technological disruption.

3.1.3 Firm performance measures

The main goal of this research is to examine how board diversity in times of technological disruption affects firm performance. Firm performance metrics not only reflect the financial health of a company but also its operational efficiency, both of which can be significantly influenced by the strategic decisions made by its board. It is very important to choose metrics that can reliably capture the impact of internal dynamics and external factors on a firm’s success.

This paper focuses on 2 primary performance metrics. Namely, return on assets (*ROA*), return on equity (*ROE*). Data on these variables is derived from Compustat. *ROA* is calculated as follows:

$$ROA_{i,t} = \frac{Net\ income_{i,t}}{Total\ assets_{i,t}}$$

where *i* represents the company of the variable and *t* the respective year. *ROA* is a key indicator of how efficiently a firm can convert the money invested in assets into profits. This metric is crucial for our analysis as it provides a clear picture of operational efficiency without the distortion of a firm's financing structure. In the context of board diversity, ROA will help assess whether diverse boards contribute to better asset utilization and operational decisions, especially during technological disruptions.

ROE is calculated as follows:

$$ROA_{i,t} = \frac{Net\ income_{i,t}}{Shareholder's\ Equity_{i,t}}$$

where *i* represents the company of the variable and *t* the respective year. *ROE* measures the profitability of a firm relative to shareholder equity. It is particularly relevant for evaluating how effectively management uses equity financing to grow earnings, and thus, is an excellent indicator of managerial effectiveness and strategic decision-making capabilities. Given the focus on board diversity, ROE will shed light on whether diverse boards enhance decision-making that maximizes shareholder returns.

3.1.4 Control variables

Finally, this paper incorporates the following control variables: firm size (*size*), debt-to-equity ratio (*de_ratio*), research & development as a percentage of sales (*rd_sales*), market conditions (*year*), and firm age (*age*). All data on these variables is directly derived from Compustat, or the variables has been constructed with the help of Compustat data.

Firm size serves as a proxy for how big a firm is and is calculated as follows:

$$size_{i,t} = \ln(\,market\ value\ of\ firm\ in\ millions)\ \$\ )$$

where i represents the company of the variable and t the respective year. Taking the natural logarithm of market value reduces the relative difference between small and large firms. This makes it easier to compare firms of different sizes within the same statistical model, ensuring that the size effect does not disproportionately influence the analysis.

Debt-to-equity ratio is calculated as follows:

$$de\_ratio_{i,t} = \frac{Total\ Debt_{i,t}}{Total\ Shareholder's\ Equity_{i,t}}$$

where *i* represents the company of the variable and *t* the respective year. This metric is an indicator of financial leverage and shows the level of company debt relative to its shareholder's equity.

Research & development as a percentage of sales is calculated as follows:

$$rd\_sales_{i,t} = \frac{Total\ R\&D\ expenditures_{i,t}}{Total\ Revenue_{i,t}}$$

where *i* represents the company of the variable and *t* the respective year. This metric serves as a great proxy for a firm's commitment to innovation. A firm with a high research & development cost might be better prepared to thrive in technological disruptions. Therefore, including the r&d/sales ratio as a control variable is essential to ensure that the analysis accurately captures the influence of board diversity on firm performance, distinct from the effects of ongoing innovation efforts.

To determine firm age, we used a similar method as Jenter and Lewellen (2015). We first identified the initial year each firm appeared in the Compustat database. Firm age was then calculated as the difference between this initial observation year and the year corresponding to each observation in our dataset. While this method has its limitations, it provides an effective proxy for firm age, suitable for our analytical purposes.

Finally, we incorporate the market conditions into our analysis by the setup of our fixed effects model. We assume that market conditions remain rather stable within a specific year, which allows us to use the year as a practical proxy for these conditions. This way, we try to control for annual variations in economic climate that could affect firm performance, such as fluctuations in interest rates, changes in regulatory policies, or shifts in consumer demand. Including the year in our model helps isolate the effects of board diversity and technological disruptions from those potentially caused by these broader market trends. We believe that this method, while not capturing every nuance of economic change, provides a sufficiently accurate reflection of the overall market environment in which the firms operate, thereby enhancing the reliability of our findings.

3.1.5 Descriptive statistics

Merging all databases yields a final sample of 25,706 observations. This sample contains data on firm performance, board characteristics, technological disruptions, and all control variables, ranging from 2011-2019 for 4,635 US firms. Moreover, the variables ROA, ROE, board diversity indexes, the single components of the board diversity indezes, and debt-to-equity ratios were winsorized at the 1% and 99% thresholds to minimize the impact of outliers, enhancing the robustness of our statistical analysis. This is particularly relevant for our measures of financial performance and leverage, where extreme values can skew results and obscure typical firm behaviours.

As you can see in table 1, the return on assets, with a mean of 1.9% and a higher median of 8.2%, varies significantly across firms ranging from -115.3% to 39.5%. For return on equity, we find a negative mean of -12.5%, possibly indicating very high leverage for some firms as the values range from -456.7% to 104.4%. The median *roe* is more in line with the return on assets at 6.7%.

The board diversity index has a mean value of 0.033 ranging from -0.9 to 1.225 showcasing the diversity in board composition across firms. The alternative board diversity index has a slightly higher mean of 0.047 and ranges from -1.217 to 1.551.

Considering the single components of the board diversity index, we find that in our sample on average 13.2% of board member are females, and that 9.1% comes from a different country. The standard deviation of age across board members fluctuates quite a lot ranging from 2.9 to 14.5. Furthermore, we also find that the standard deviation of board tenure fluctuates heavily ranging from 0 to 15.1.

For our technological disruption dummy, the mean of 0.194 implies that 19.4% of the observations in our sample are classified as a “technological disruption.” Looking at the extreme specification of a technological disruption, we only find 1.3% of observations in our sample classified as a “technological disruption.”

Looking at the control variables you can see that there is a diverse group of firms with regards to size in our samples as the natural logarithm of market value in millions for the sample firms ranges from 2.211 to 11.727. The debt-to-equity ratio of our sample firms varies greatly as well from -8.591 to 24.728. The negative minimum values seen in the debt-to-equity ratio suggests some firms faced conditions where total liabilities surpassed total assets, potentially due to significant losses, restructuring, or adverse market conditions. This underscores the variability in financial health and leverage practices across the sample. The mean and median value of this ratio are 2.641 and 1.219 respectively. For research & development costs as a percentage of sales, looking at just the average will give a very skewed reflection of reality. The average is equal to 0.93 which implies that on average firms spend 93% of sales on research & development. However, when considering that the median is 0 and that the values range from 0 to 47.899, this high average is caused due to some extreme outliers in our sample, and most sample firms spend 0% of sales on research & development. Looking at *age*, the age of firms in our sample ranges from 0 to 51, with mean 19.64 and median 18. This makes sense, as we are not necessarily looking at just startups, but also at a lot of established firms.

Table 1

Descriptive statistics sample

	Mean	Median	Std. Dev.	Min	Max
roa	0.019	0.082	0.252	-1.153	0.395
roe	-0.125	0.067	0.714	-4.567	1.044
board_diversity index	0.033	0.005	0.446	-0.900	1.225
alt_board_diversity_index	0.047	0.021	0.559	-1.217	1.551
female_ratio	0.132	0.125	0.113	0	0.444
sd_age	7.757	7.5	2.423	2.9	14.5
int_ratio	0.091	0	0.170	0	0.6
sd_timeboard	4.672	4.4	3.605	0	15.1
technological_disruption	0.194	0.000	0.396	0	1
extr_technological disruption	0.013	0	0.113	0	1
size	6.697	6.704	2.059	2.211	11.727
de_ratio	2.641	1.219	4.150	-8.591	24.728
rd_sales	0.930	0.000	5.494	0.000	47.899
age	19.640	18.000	14.493	0.000	51.000

Note: The full panel consists of 25,706 observations and 4,635 US firms. roa roa, roe, board_diversity_index, alt_board_diversity_index, female_ratio, sd_age, int_ratio, sd_timeboard, size, de_ratio, rd_sales are winsorized at 1%.

3.2 Statistical methods and regression analysis

To analyse the impact of board diversity on firm performance during times of technological disruption this paper will use panel data econometric techniques. These methods are appropriate for data involving multiple observations over time for the same firms, allowing us to control for both observable and unobservable firm-specific effects.

3.2.1 Model specification

More specifically, we will use a fixed effects model. This model is particularly effective for our analysis as it excels in controlling for latent heterogeneity among firm characteristics that do not vary over time but could potentially confound the observed relationships. By employing the fixed effects model, we ensure that our analysis accounts only for internal firm dynamics and external industry-wide shifts, rather than being biased by unobservable firm-specific attributes that do not change over time. This method provides a clear, undistorted view of the causal relationships we aim to explore, thus enhancing the validity of our findings.

The regression formula that this paper will utilize is as follows:

$$roa_{i,t} = \beta_0 + \beta_1 * BD_{i,t} + \beta_2 * TD_{i,t} + \beta_3 * BD_{i,t} * TD_{i,t} + \beta_3 * \textbf{Control Variables} + \varepsilon_{\mathrm{i,t}}$$

, when taking return on assets as a proxy for firm performance, and:

$$roe_{i,t} = \beta_0 + \beta_1 * BD_{i,t} + \beta_2 * TD_{i,t} + \beta_3 * BD_{i,t} * TD_{i,t} + \beta_3 * \textbf{Control Variables} + \varepsilon_{\mathrm{i,t}}$$

, when taking return on equity as a proxy for firm performance, where:

- $roa_{i,t}$ represents the return on assets for firm *i* time t.
- $roe_{i,t}$ represents the return on equity for firm *i* time t.
- $BD_{i,t}$ represents the board diversity index firm *i* time t.
- $TD_{i,t}$ represents the technological disruption dummy index firm *i* time t.
- $BD_{i,t} * TD_{i,t}$ represents the interaction term between the board diversity index and the technological disruption dummy.
- $\textbf{Control Variables}$ represents the control variables, size of firm, age of firm, debt-to-equity ratio, and market conditions.

Additionally, we will investigate the effects of each single component of the board diversity index. This will be another fixed effects model containing each single component as an independent variable and the interaction term between each component and the technological disruption dummy.

The regression analysis will be performed using Stata, which provides comprehensive tools for panel data analysis.

3.2.2 Robustness checks

To ensure the reliability of our findings, this paper incorporates several robustness checks. These checks are designed to test the stability of our results under alternative specifications and definitions.

Firstly, this paper uses 2 different proxies for firm performance. Namely, return on assets, and return on equity.

Secondly, this paper uses 2 definitions for the board diversity index. The regular index consists of all four components of board diversity: age diversity, gender diversity, nationality diversity, and board tenure diversity. The alternative board diversity index focuses only on the 2 components: age diversity and gender diversity.

Finally, we define a technological disruption in 2 different ways. Firstly, the dummy variable is equal to 1 if the *patent_weight* for a specific industry in a specific year is bigger than the mean + standard deviation of the *patent_weight* for that industry. Secondly, we will only label a period as a technological disruption in more extreme cases. This implies that the dummy variable is equal to 1 if the *patent_weight* for a specific industry in a specific year is bigger than the mean + 2* standard deviation of the *patent_weight* for that industry. And as mentioned previously, the technological disruption dummy will also be constructed based on the median instead of the mean.

3.2.3 Model interpretation

The goal of the regression analysis is to identify the impact of board diversity on firm performance in times of technological disruption. Coefficient β_1 will reflect the direct impact of board diversity on firm performance. β_2 will reflect the direct impact of a technological disruption on firm performance. Our main coefficient of interest is β_3 which reflects the effect of board diversity on firm performance modulated by the presence of a technological disruption. For assessing statistical significance, this study adopts a threshold of $p < 0.05$. Coefficients with p-values below this threshold will be considered statistically significant, indicating a robust influence of the corresponding variables on firm performance.

4. Results

4.1 Regular regressions

Table 2 shows the results for the first regressions, where we use our regular board diversity index and regular definition of a technological disruption. We find a negative coefficient for the interaction for both, the *roa* model (-0.00672), and the *roe* model (-0.0355). This implies that there is a negative relationship between board diversity in times of technological disruption, and firm performance. For *roa*, this relationship is insignificant with a p-value of 0.055 However for *roe*, there is a significant relationship with a p-value of 0.037. Looking at the variables, board diversity and technological disruption, in isolation, we find a positive relationship with firm performance, implying the more diverse a firm, or if there is a technological disruption, firm performance will increase for the firms in our sample. Significance differs for our 2 models, in model 1 we only find a significant relationship for the technological disruption dummy, and in model 2 only for the board diversity index. For the control variables, we find a positive relationship for firm size and their debt-to-equity ratio with firm performance. This implies the bigger the firm and the higher the firm's debt-to-equity ratio, the better firm performance. For model 1, this relationship is only significant for firm size, and for model 2, both control variables have a significant relationship. The other 2 control variables: research & development as a percentage of sales, and firm age, have a negative relationship with firm performance. This relationship is significant in model 1 and in model 2 only the firm age coefficient is significant. As can be seen in table 8 in the appendix, the regressions using the technological disruption dummy based on the median yield very similar results.

Table 2

Fixed effects regression results with regular board diversity index and regular technological disruption dummy.

	roa		*roe*	
	Model 1		*Model 2*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
BD	0.00368	0.200	0.0320*	0.022
TD	0.00452*	0.007	0.0159	0.052
*BD*TD*	-0.00672	0.055	-0.0355*	0.037
size	0.0439*	0.000	0.208*	0.000
de_ratio	0.000385	0.096	0.00391*	0.001
rd_sales	-0.00330*	0.000	-0.000397	0.618
age	-0.00590*	0.000	-0.0292*	0.000
Intercept	-0.158*	0.000	-0.953*	0.000
observations	25706		25706	
R-sqaured	0.0877		0.0705	

*Note: BD = board diversity index, TD = technological disruption dummy, BD*TD = interaction term between board diversity index and technological disruption dummy. If p-value <0.05: **

4.2 Alternative board diversity index

As can been seen in Table 3, when using the alternative board diversity index, we again find a negative relationship between the interaction term and firm performance. However, in this case both the coefficients for *roa* and *roe* are insignificant. Similarly, as in model 1 and 2, we find a significant positive relationship between the technological disruption dummy and *roa*, and a significant positive relationship between the diversity index and *roe*. For the control variables we find the same direction of the relationships as in model 1 and 2, and again, *de_ratio* in model 3 and *rd_sales* in model 4 are insignificant. Also here, as can be seen in table

9 in the appendix, the regressions using the technological disruption dummy based on the median yield very similar results.

Table 3

Fixed effects regression results with alternative board diversity index and regular technological disruption dummy.

	roa		*roe*	
	Model 3		*Model 4*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
alt_BD	0.00372	0.067	0.0368*	0.022
TD	0.00434*	0.010	0.0154	0.061
*alt_BD*TD*	-0.00524	0.062	-0.00698	0.610
size	0.0439*	0.000	0.208*	0.000
de_ratio	0.000382	0.098	0.00388*	0.001
rd_sales	-0.00330*	0.000	-0.000410	0.607
age	-0.00593*	0.000	-0.0300*	0.000
Intercept	-0.158*	0.000	-0.944*	0.000
observations	25706		25706	
R-sqaured	0.0877		0.0705	

*Note: alt_BD = alternative board diversity index, TD = technological disruption dummy, alt_BD*TD = interaction term between alternative board diversity index and technological disruption dummy. If p-value <0.05: **

4.3 Extreme classification of technological disruption

Furthermore, we utilized a more extreme definition of technological disruption for all models. This means that we classify a period as a technological disruption if that the dummy variable is equal to 1 if the *patent_weight* for a specific industry in a specific year is bigger than the mean + 2* standard deviation of the *patent_weight* for that industry. In table 4 you can see that, in the case of using a regular board diversity index, the coefficient of *BD*extreme_TD* is positive. However, for both the *roa* and *roe* model, the coefficient is highly insignificant. Thus, it is fair to say that there is no relationship between board diversity in times of extreme technological disruption and firm performance. All the other main variables of interest (board diversity and disruption dummy) are also highly insignificant in model 5 and 6, except board diversity in the *roe* model. This implies that board diversity has a significant positive relationship with return on equity based on this model. For the control variables, we again find very similar results as in model 1-4. All control variables are highly significant, except *de_ratio* in the *roa* model and *rd_sales* in the *roe* model.

Table 4

Fixed effects regression results with regular board diversity index and extreme technological disruption dummy.

	roa		*roe*	
	Model 5		*Model 6*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
BD	0.00260	0.354	0.0269*	0.049
extreme_TD	0.00223	0.680	0.00131	0.960
*BD*extreme_TD*	0.00316	0.800	0.00821	0.893
size	0.00439*	0.000	0.208*	0.000
de_ratio	0.000381	0.099	0.00389*	0.001
rd_sales	-0.00330*	0.000	-0.000404	0.613
age	-0.00621*	0.000	-0.0306*	0.000
Intercept	-0.151*	0.000	-0.927*	0.000
observations	25706		25706	
R-sqaured	0.0873		0.0702	

*Note: BD = board diversity index, extreme_TD = extreme technological disruption dummy, BD*extreme_TD = interaction term between (alternative) board diversity index and extreme technological disruption dummy. If p-value <0.05: **

Table 5 shows the results for the extreme definition of technological disruption, however, in this case, the alternative board diversity index is used. We find very similar results as in model 5 and 6. The interaction terms are highly insignificant, and the same holds for the board diversity and technological disruption variables in isolation. We only see significant for the alternative board diversity variable in the *roe* model. Looking at significance and direction of the control variables, we again find very similar results as in the previous models. Again, as can be seen in table 10-11 in the appendix, the regressions using the technological disruption dummy based on the median yield very similar results as model 5-8.

Table 5

Fixed effects regression results with alternative board diversity index and extreme technological disruption dummy.

	roa		roe	
	Model 7		*Model 8*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
alt_BD	0.00297	0.132	0.0367*	0.000
extreme_TD	0.00172	0.753	-0.00127	0.962
*alt_BD*extreme_TD*	0.00770	0.432	0.0358	0.453
size	0.0439*	0.000	0.208*	0.000
de_ratio	0.000379	0.101	0.00386*	0.001
rd_sales	-0.00330*	0.000	-0.000421	0.598
age	-0.00625*	0.000	-0.0312*	0.000
Intercept	-0.151*	0.000	-0.917*	0.000
observations	25706		25706	
R-sqaured	0.0873		0.0707	

*Note: alt_BD = alternative board diversity index, extreme_TD = extreme technological disruption dummy, alt_BD*extreme_TD = interaction term between alternative board diversity index and extreme technological disruption dummy. If p-value <0.05: **

4.4 Single component regression

Lastly, this paper investigated the effects of each single component of the board diversity index. In table 6 you can see that there is a positive effect for *female_ratio, sd_age,* and *int_ratio* on *roa*. *sd_timeboard* has a negative effect. However, only the effects of *female_ratio* and *sd_timeboard* are statistically significant. Looking at *roe* in model 10, we see a slight difference with *int_ratio* having a negative effect. However, for this model, only *female_ratio* and *sd_age* are statistically significant. Looking at the interaction terms we find a significant negative impact of *female_ratio* during times of technological disruption on firm performance in model 9, and a significant negative impact of *sd_timeboard* during times of technological disruption on firm performance in model 10.

Using the extreme definition of technological disruption, in table 7, we see no significant relationship in the *roa* model (model 11). In model 12 we find that *female_ratio, sd_age,* and*,* *sd_timeboard* have a significant positive impact on *roe*. The interaction terms show no significant effects.

Table 6

Fixed effects regression results with single components of board diversity index and regular technological disruption dummy

	roa		*roe*	
	Model 9		*Model 10*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
female_ratio	0.0244*	0.025	0.184*	0.001
sd_age	0.000439	0.367	0.00471*	0.047
int_ratio	0.00649	0.387	-0.0085695	0.815
sd_timeboard	-0.00102*	0.05	-0.00453	0.075
TD	0.00884	0.137	0.0245	0.397
*female_ratio*TD*	-0.0456*	0.002	-0.128	0.072
*sd_age*TD*	0.0000999	0.873	0.00422	0.167
*int_ratio*TD*	-0.0159	0.099	-0.00794	0.865
*sd_timeboard*TD*	0.000234	0.582	-0.00539*	0.009
size	0.0439*	0.000	0.208*	0.000
de_ratio	0.000374	0.106	0.00389*	0.001
rd_sales	-0.00330*	0.000	-0.000399	0.617
age	-0.00591*	0.000	-0.0299*	0.000
Intercept	-0.1608*	0.000	-0.985*	0.000
observations	25706		25706	
R-sqaured	0.0884		0.0716	

*Note:, TD = regular technological disruption dummy, component*TD = interaction term between component index and regular technological disruption dummy. If p-value <0.05: **

Table 7

Fixed effects regression results with single components of board diversity index and extreme technological disruption dummy

	roa		*roe*	
	Model 11		*Model 12*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
female_ratio	0.0190	0.077	0.171*	0.001
sd_age	0.000444	0.342	0.00555*	0.015
int_ratio	0.00460	0.532	-0.00848	0.813
sd_timeboard	-0.000966	0.058	-0.00611*	0.014
extreme_TD	-0.0164	0.445	-0.104	0.321
*female_ratio*extreme_TD*	0.0126	0.797	-0.0365	0.878
sd_age extreme_TD*	0.00237	0.277	0.0156	0.143
int_ratio extreme_TD*	-0.0161	0.683	-0.0877	0.647
sd_timeboard extreme_TD*	-0.0000826	0.955	-0.000878	0.903
size	0.0439*	0.000	0.208*	0.000
de_ratio	0.000375	0.105	0.00384*	0.001
rd_sales	-0.00330*	0.000	-0.000421	0.597
age	-0.00621*	0.000	-0.0307*	0.000
Intercept	-0.153*	0.000	-0.963*	0.000
observations	25706		25706	
R-sqaured	0.0876		0.0710	

*Note: extreme_TD = extreme technological disruption dummy, component*extreme_TD = interaction term between component and extreme technological disruption dummy. If p-value <0.05: **

5. Discussion

5.1 Board diversity

In all our models we find a positive significant relationship between (alternative) board diversity and return on equity. For return on assets, we also find a positive relationship, however this relationship is not significant. Based on these results, there seems to be some positive relationship between board diversity and firm performance. This is in line with the findings of Khidmat et al. (2020) where they found that gender and nationality diversity have significant positive effect on firm performance. This paper has opposite results to Brahma et al.

(2020) and Frijns et al. (2016) which found a negative relationship between board diversity and firm performance. These findings underscore the importance of the sample and metrics you use in your research. Previous literature has found opposing results, and in this study we see a difference in significance if we compare our models using *roa* and *roe* as a proxy for firm performance. This makes it very difficult to make general statements about the impact of board diversity on firm performance as it seems to be different in each scenario.

5.2 Technological disruption

Interestingly, technological disruption has a positive relationship with firm performance in all our models. This relationship is significant in model 1 and 3 where we use *roa* as a proxy for firm performance and the regular definition of a technological disruption. It is insignificant, but still positive for all other models. This positive relationship implies that, on average, being in a technologically disruptive period has a beneficial effect on firm performance. However, it is crucial to recognize that technological disruptions typically result in both winners and losers. The positive average effect observed may be driven by a subset of firms that are particularly well-positioned to leverage these disruptions. These firms might include those with robust innovation capabilities, strong financial health, or those directly benefiting from new technologies. Furthermore, the impact of technological disruption on firm performance can vary over time. Initially, the impact might be challenging and even detrimental for some firms. However, the long-term benefits of adapting to new technologies might lead to positive outcomes that are reflected in the observed data.

5.3 Board diversity in times of technological disruption

Finally, our models do not seem to find a consistent relationship between board diversity in times of technological disruptions and firm performance. This paper had the following hypothesis: "*Board diversity will have a positive impact on firm performance in times of technological disruptions.*". This was based on the research done by Miller and Del Carmen Triana (2009) and Rodríguez-Gulías et al. (2023). They found that diversity has a positive impact on innovation. We assumed that firms with better innovative capabilities will do a better job at navigating through disruptive periods. In model 1-4 we find the opposite. Namely, board diversity in times of technological disruption has a negative effect on firm performance. This relationship is significant at the 5% level in model 2 and significant at the 10% level in model 1 and 3. This counterintuitive result might be explained by several factors. First, while diversity is generally associated with a range of perspectives and enhanced problem-solving capabilities, it can also introduce complexities into decision-making processes. During periods of technological disruption, when quick, decisive action is often necessary, the deliberative processes that diversity fosters might impede rapid decision-making. Furthermore, the stress of navigating through significant industry changes might exacerbate latent conflicts within a diverse board, leading to inefficiencies and a potential negative impact on firm performance. When looking at model 5-8, which uses the more extreme definition of a technological disruption. We find the opposite relationship. Namely, board diversity in times of technological disruption has a positive effect on firm performance. However, this relationship is highly insignificant. This lack of significance could be attributed to the relatively small number of instances classified as extreme technological disruptions. The rarity of such extreme cases can introduce substantial variability into the estimates, making it challenging to establish a clear causal relationship.

5.4 Single component regression

When investigating the effect of each single component of board diversity on firm performance we found that there is a positive significant relationship between the percentage of female members on the board and return on assets, and we found a positive significant relationship between the standard deviation of age of board members and return on equity. On the contrary, we found a negative significant relationship between that standard deviation of time that board members have been sitting on the board and return on assets. These findings are in line with the findings of Brahma et al. (2020) who found a positive significant relationship between gender diversity and firm performance, and with the findings of Fernández and Gaite (2020) who found that age diversity has a positive impact on firm performance.

The coefficients of the interaction terms show the effect on each component in times of technological disruption. In our model for the extreme definition of technological disruption we find no significant coefficients. However, in model 9 and 10, which uses the regular definition of technological disruption, we find a significant negative relationship for *female_ratio*TD* and *sd_timeboard*TD*. *female_ratio*TD* is significant at the 5% level in model 9, and significant at the 10% level in model 10. *sd_timeboard*TD* is significant at the 5% level in model 10, but heavily insignificant in model 9. This shows that during times of technological disruption, firms with more females on the board perform worse. This could be due to various reasons. A possible explanation could be that female directors have less experience on average with managing firms during technological disruptions. However, to come to a true conclusion on why we find these results, more research must be done. As we find such different results for *sd_timeboard*TD* it is difficult to draw conclusions on the impact of the standard deviation of time on board of board members as it heavily depends on the data you use. According to model 10, we would say that the bigger the standard deviation, the worse firm performance in times of technological disruption. But again, the results depend heavily on the data.

5.5 Limitations

Despite these insights, our study is not without its limitations. Firstly, the measure of technological disruption based on patent data, while innovative, may not capture all aspects of how such disruptions affect the industry landscape. Future research could try to capture these aspects in other ways. For example, by incorporating market reactions or changes in consumer behaviour. This might provide a more comprehensive understanding of how disruptions affect firm performance. Secondly, even though this study covers different industries, the effects observed might not be universal across all sectors. Each industry can experience the effects of a technological disruption in a unique way due to their unique market dynamics and operational structures. Also, the results of this study and of previous literature show that the effects are not consistent across different samples and methodologies. This undermines the need to interpret the results with caution as they seem to be heavily depended on the data you use.

6. Conclusion

The goal of this paper was to identify the impact of board diversity on firm performance in times of technological disruption. Previous research has mostly shown that board diversity increases firm performance in general. Various components of board diversity seem to impact firm performance in a positive way. For example, by increased productivity, increased corporate social responsibility, or increased investment efficiency. However, it is important to note that some research has found the opposite effect of board diversity on some firm outcomes. Until this study, no research had been undertaken specifically on the effect of board diversity on firm performance in times of technological disruption. Even though some researchers have investigated the effects of board diversity on innovation, which they found they found to be positive, this has never been linked to better navigation through times of technological disruption. Therefore, the question that was studied in this paper was: *"How does board diversity impact firm performance during times of technological disruption?"*

To answer this research question, comprehensive data was gathered on board characteristics, firm performance and characteristics, and patents. Patent information, derived from the US Patent and Trademark Office, served as the foundation for constructing a technological disruption dummy variable. This variable reflects whether significant technological disruptions occurred within an industry each year, based on the volume of patents granted and the extent of their citations relative to other years. The analysis utilized a fixed effects regression model to meticulously explore the influence of board diversity on firm performance during periods of technological upheaval. This model ensured that any unobserved heterogeneity could be controlled, thus isolating the effects of board diversity from other latent factors that could skew the results. The findings from the main models 1-4 revealed a negative effect of board diversity on firm performance during times of technological disruption. This relationship was significant at the 5% level for model 2 and significant at the 10% level for model 1 and 3. Models 5-8 which used a more extreme definition of a technological disruption showed the opposite effect. However, these results were highly insignificant. This suggests that diverse boards may diminish a firm's ability to navigate through times of technological disruption.

The implications of this study are significant for corporate governance, and particularly for firms operating in highly dynamic sectors. Previous literature has shown how board diversity often improves firm outcomes. This study argues this by showing the negative impact of board diversity in times of technological disruptions.

Unfortunately, this study is not without its limitations. The methodology of defining a technological disruption based on patent data might not capture the full spectrum of innovation and market dynamics that constitute to a disruptive environment. Future research could expand on this by incorporating alternative measures of technological disruption. For example, technological advancements that do not results in patents, or also considering the adaption rates of certain technologies across industries.

Furthermore, the results are very dependent on the data set used. This questions the generalizability of the results, as we have found opposing results by using a different measure for technological disruption in this paper. Also, in previous literature we see inconsistent results on board diversity impact on firm outcomes, where one study finds a positive effect whilst another study finds a negative effect. Even though the results are inconsistent, they mostly lean to a positive effect of firm performance, but it is important to keep this in mind when looking at different contexts.

All in all, this research contributes to a nuanced understanding of how board diversity influences firm performance, particularly during times of technological disruption. While the findings show a negative impact of diversity under certain conditions, it should be kept in mind that the results could differ in a different context.

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Appendix

Table 8

Fixed effects regression results with regular board diversity index and regular median technological disruption dummy.

	roa		*roe*	
	Model 13		*Model 14*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
BD	0.00254	0.379	0.0316*	0.024
med_TD	0.00712*	0.000	0.0263*	0.002
*BD*med_TD*	-0.00577	0.101	-0.0379*	0.027
Size	0.0440*	0.000	0.208*	0.000
de_ratio	0.000393	0.089	0.00394*	0.000
rd_sales	-0.00330*	0.000	-0.000409	0.608
Age	-0.00565*	0.000	-0.0286*	0.000
Intercept	-0.164*	0.000	-0.972*	0.000
observations	25706		25706	
R-sqaured	0.0881		0.0708	

*Note: BD = board diversity index, med_TD = median technological disruption dummy, BD*med_TD = interaction term between board diversity index and median technological disruption dummy. If p-value <0.05: **

Table 9

Fixed effects regression results with alternative board diversity index and regular median technological disruption dummy.

	roa		*roe*	
	Model 15		*Model 16*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
alt_BD	0.00283	0.164	0.0360*	0.000
med_TD	0.00699*	0.000	0.0258*	0.002
*alt_BD*med_TD*	-0.00402	0.153	-0.00503	0.714
Size	0.0440*	0.000	0.208*	0.000
de_ratio	0.000391	0.091	0.00391*	0.001
rd_sales	-0.00330*	0.000	-0.000414	0.603
Age	-0.00568*	0.000	-0.0292*	0.000
Intercept	-0.164*	0.000	-0.965*	0.000
observations	25706		25706	
R-sqaured	0.0881		0.0710	

*Note: alt_BD = alternative board diversity index, med_TD = median technological disruption dummy, alt_BD*med_TD = interaction term between alternative board diversity index and median technological disruption dummy. If p-value <0.05: **

Table 10

Fixed effects regression results with regular board diversity index and extreme median technological disruption dummy.

	roa		*roe*	
	Model 17		*Model 18*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
BD	0.00160	0.568	0.0251	0.066
med_extreme_TD	0.00976*	0.013	0.0129	0.501
*BD*med_extreme_TD*	-0.00736	0.378	-0.0283	0.487
Size	0.0438*	0.000	0.208	0.000*
de_ratio	0.000392	0.091	0.00391	0.001*
rd_sales	-0.00330*	0.000	-0.000399	0.617
Age	-0.00509*	0.000	-0.0304	0.000*
Intercept	-0.153*	0.000	-0.930	0.000*
observations	25706		25706	
R-sqaured	0.0875		0.0702	

*Note: BD = board diversity index, med_extreme_TD = extreme median technological disruption dummy, BD*med_extreme_TD = interaction term between board diversity index and extreme median technological disruption dummy. If p-value <0.05: **

Table 11

Fixed effects regression results with alternative board diversity index and extreme median technological disruption dummy.

	roa		*roe*	
	Model 19		*Model 20*	
	Coeff.	*p-values*	*Coeff.*	*p-values*
alt_BD	0.00227	0.250	0.0349*	0.000
med_extreme_TD	0.00969*	0.013	0.0120	0.530
*alt_BD*med_extreme_TD*	-0.00431	0.524	0.0184	0.577
Size	0.0438*	0.000	0.208*	0.000
de_ratio	0.000389	0.093	0.00387*	0.001
rd_sales	-0.00330*	0.000	-0.000416	0.602
Age	-0.00611*	0.000	-0.0310*	0.000
Intercept	-0.153*	0.000	-0.921*	0.000
observations	25706		25706	
R-sqaured	0.0875		0.0706	

*Note: alt_BD = alternative board diversity index, med_extreme_TD = extreme median technological disruption dummy, BD*med_extreme_TD = interaction term between alternative board diversity index and extreme median technological disruption dummy. If p-value <0.05: **