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Does size matter? – Employee Happiness in Entrepreneurial Firms

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Thomas Franciscus Quirinus (Tommy) van Toor

t.f.q.vantoor@students.uu.nl

7208677

Abstract: This paper explores the relationship between Entrepreneurial Orientation (EO) and Employee Happiness (EH) in large public companies, including the abruptness of change in the level of EO and the role of firm size. The central research question investigates how the level and abruptness of changes in EO, affect EH and whether firm size moderates these effects. To address this, a longitudinal dataset from the S&P 500 companies (2016-2020) was analyzed using fixed effects regression models with robust standard errors. The main finding reveals a positive relationship between EO and EH, indicating that EO's emphasis on innovation, risk-taking, and employee autonomy enhances EH. While initial findings suggested that abrupt changes in EO negatively impact EH, further analysis indicated that this effect might be influenced by other factors. The study concludes that while EO can improve EH, abrupt changes in EO could risk the overexploitation of human resources.

Keywords: *Entrepreneurial Orientation, Employee Happiness, Firm size, Panel Data*

Universiteit Utrecht

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Supervisor

Dr. C.J. Rigtering

j.p.c.rigtering@uu.nl

Co-reader

Dr. M. Grève

m.greve@uu.nl

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1. Introduction

Employee happiness (EH) is a major topic in academic literature, closely related to job satisfaction, engagement and employee well-being (Fisher, 2010). Companies with high EH tend to perform better (Oswald et al., 2015) and can even be used as a performance predictor (Harrison et al., 2006; Riketta, 2008). Therefore, firms see a high EH not just as an ethical requirement but also as a strategic asset. That is why the number of companies focussing their business model around improving the EH of their clients has increased a lot (Effectory, 2024; Eletive, 2024; quantumworkplace.com, 2024). The increased firm performance is caused by happier employees leading more satisfied customers, increasing customer loyalty and higher revenues (Harvard Business Review, 2019). However, a recent Bloomberg report shows that EH is currently at an all-time low globally, but in the US specifically (Bloomberg, 2023). This decline impacts individual well-being, but also has broader societal implications, such as increased healthcare costs and lower productivity (McKinsey Health Institute, 2024). That is why the World Economic Forum stresses the importance of employee mental health, in an attempt to boost the economy and reduce future health care costs (World Economic Forum, 2019, 2024).

Similarly, much research has focussed on the relationship between *entrepreneurial orientation* (EO) and business performance. EO is a firm-level strategy set out by top-management, often characterized by the level of innovativeness, risk-taking, proactiveness, employee autonomy and competitive aggressiveness of a firm (Lumpkin & Dess, 1996). Initially, EO was thought to positively affect business performance, but these results were heavily reliant on cross-sectional data (Lomberg et al., 2017) and often included survival bias (Rauch et al., 2009; Schweiger et al., 2019). Recent studies show that firms with a high level of EO have a lot of variance in their business performance (Patel et al., 2015; Wiklund & Shepherd, 2011). Given the unpredictable effects of EO, its relationship with other firm characteristics should be explored. Top-managers that understand the key conditions for EO can make better and more informed decisions, increasing the likelihood of a successful EO strategy.

For a successful EO strategy, it must pervade the entire firm and sustain over time (Hornsby et al., 2013; W. Wales et al., 2011). This means that for a successful EO strategy affects all employees. It is therefore remarkable that the relationship between EO and EH remains underexplored in current academic literature. This is significant because both EO and EH affect business performance and low EH could negate the potential benefits from the EO strategy. Previous studies on the EO-EH relationship has yielded mixed results. EO often provides employees with autonomy and resources. For some, this increases organizational commitment and job satisfaction (De Clercq & Rius, 2007; Soomro & Shah, 2019), while causing stress for others due to performance pressure without linear instructions (Andersén, 2017; Monsen & Wayne Boss, 2009).

In 2023 Gali et al. introduced the *Resource Exhaustion Theory* (RET) in a paper about the relationship between EO and firm failure. While EH is not mentioned specifically, some components of this theory may apply on the EO-EH relationship. The RET suggests that EO the chance of firm failure significantly increases in a lot of circumstances. They state that every firm has *Entrepreneurial Entropy* (EE) which is a measure for the level of resource exhaustion due to insufficient returns on investments in business activities. If a firm has a very high level of EO, a high level of EO for a long time or an abrupt shift in their level of EO, the EE significantly increases. The reason for the increase in EE is that the EO strategy prioritizes the exploration of business opportunities, neglecting the exploitation of these opportunities. The firm keeps investing resources, without generating the necessary returns. When the firm becomes aware of this problematic pattern, they try to counteract this by abruptly changing their EO strategy. The abrupt change in the level of EO at firm level changes the job demands and thus requires the employees to adapt their work behaviour. Another reason why the EO level might suddenly change is with the appointment of a new CEO (Engelen et al., 2015; Grühn et al., 2017). A new CEO is often brought in to break the patterns of its predecessor and has the confidence in his ability to change the firm successfully.

An abrupt change in EO will increase EE, regardless of the cause, whether it suddenly increases or decreases. This is due to the significant investments required for the employees to adapt to the organizational change. Furthermore, human resources can be exhausted just like every other resource, negatively impacting work engagement and job performance (Bakker & Demerouti, 2014). The required flexibility from employees to adapt could therefore take a toll on the EH.

Firm size is often mentioned in regards to EO. Bigger firms have more resources available for the EO strategy (Gali et al., 2023) and knowledge on how to recognize and capitalize on new business opportunities (Eshima & Anderson, 2017). Yet, in bigger organizations top-management often struggles for alignment throughout the company (Harvard Business School, 2018). Because alignment is key for the EO strategy to be successful (Hornsby et al., 2013; W. Wales et al., 2011), the role of firm size for the EO-EH relationship might be different than for the relationship between EO and business performance.

Both EO and EH affect business performance, but their relationship remains unclear. Past literature that has looked into the EO-EH relationship lacked multiple moments through time and thus could not include the effect of an abrupt change in EO. The role of firm size has been addressed in EO literature, but effect of firm size on the relationship with business performance does not seem to transfer to the relationship with EH. The central research question in this paper is therefore: *"What is the effect of the level of Entrepreneurial Orientation, and the abruptness of change in the level of Entrepreneurial Orientation, on Employee Happiness, and how does firm size affect these effects?"*.

The answer to this question will help top-managers that want to change the EO-level of their firm, to assess the current situation and consider the potential consequences for their employees. Although a change in the level of EO might seem attractive from a business perspective, the employees must be able to handle this change. Otherwise firms experience a significant drop in their EH, followed by a drop in the individual and overall business performance.

To come to the answer for research question, this study starts in the next chapter with the theoretical background. Here, the most important papers and theories regarding EO and EH will be discussed, resulting in the hypotheses. The third chapter is the method section. This chapter contains the data description, operationalization of the variables and an explanation of the theoretical approach. The method section will be followed by the results in the fourth chapter. Based on statistical tests and regression results, the hypotheses will either be accepted or rejected. In the fifth and final chapter the results will be discussed in comparison with existing literature about entrepreneurial orientation and employee happiness.

2. Theoretical Background

2.1 Past literature

Employee Happiness

Employee happiness (EH) is a multidimensional construct that has received a lot of attention in academic literature. The three main pillars of EH are job satisfaction, engagement and well-being (Fisher, 2010). Job satisfaction represents how happy employees are with their work content and work conditions (Judge & Klinger, 2008; Locke, 1976), engagement is the level of emotional, behavioural and cognitive commitment towards the organization (Kahn, 1990; Schaufeli & Bakker, 2004a) and well-being contains the physical, social and mental health of an employee (Bakker & Demerouti, 2007; Warr, 1987). Other drivers for EH are the alignment between individual and company values (Pratt & Ashforth, 2003; Steger et al., 2012), autonomy, responsibility and decision-making power (Deci & Ryan, 2000; Hackman & Oldham, 1976), both formal and informal recognition and rewards for their effort (Deci et al., 1999; Eisenberger et al., 1986), relationships with colleagues and supervisors (Griffin et al., 2001; Schein, 2010) and lastly, growth and development opportunities in the foreseeable future (London & Smither, 1999; Noe et al., 2014). Overall, EH is the result of a combination of unique individual traits and work environment characteristics (Fisher, 2010). One intangible part of the work environment that is very important for the employee happiness are the social interactions with colleagues. During COVID-19 most employees were forced to work from home. This drastically decreased their social interactions, affecting their job satisfaction and EH (Mehta, 2021). The interactions with top-management decreased too. Employees thrive when top-management sets a clear strategy and they are supported when they need it (Grant et al., 2007; Griffin et al., 2001). When employees align with the firms strategies and feel like they have the support they require, their engagement, confidence and motivation significantly increases.

Because unique individual traits are just as important as the work environment characteristics, EH differs between individuals within the same firm. Although it is important for managers to take individual cases into account (Griffin et al., 2001), the average EH over all employees shows how well a company is doing as a firm-level characteristic (Krekel et al., 2019). To improve the general level of EH, top-managers should focus on creating a healthy and supportive work culture, set realistic job demands, while providing competent leadership and enhancing job opportunities (Fisher, 2010). This is in line with the *Job Demands-Resources Theory* (JD-R) introduced by Bakker & Demerouti (2014). JD-R states that employee well-being and performance is determined by a balance between job demands and job resources. Job demands like high work pressure, role conflict or unfavourable physical conditions should be met with sufficient job resources like autonomy, social support or performance feedback. When job demands are outweighing the job resources, firms are risking the exhaustion of their employees mental and physical resources. When the job resources outweigh the job demands, employees tend to have higher work engagement and perform better. The overall EH level is therefore for most companies a critical KPI at firm level, as firms with high levels of EH tend to have better business performance (Bellet et al., 2023; Oswald et al., 2015; Riggle et al., 2009; Thompson & Bruk-Lee, 2021).

Entrepreneurial Orientation

Entrepreneurial Orientation (EO) is a firm level construct that reflects a top-management strategy style that prioritizes development over maintaining the status quo (Anderson et al., 2015; W. J. Wales et al., 2020), providing a basis for entrepreneurial behaviour of employees (Wiklund & Shepherd, 2003). The original three dimensions for the EO construct were innovativeness, proactiveness and risk-taking (Miller, 1983), while later the dimensions competitive aggressiveness and employee autonomy were added (Lumpkin & Dess, 1996). Innovativeness reflects a firms tendency to engage in the development of new products and services, in effort to create a competitive advantage (Hurley & Hult, 1998). Proactiveness is the process of looking forward and trying to predict or shape the future in order to enhance market positioning (Parker et al., 2006). Risk-taking means that a firm is willing to invest a significant proportion of its resources in projects with uncertain outcomes. This does not mean bold and rash investments, but taking calculated risks in effort to absorb uncertainty instead of letting uncertainty paralyze the firm (Morris et al., 2008). Competitive aggressiveness is the drive to directly challenge industry competition, risking escalation but aiming for an improved market position and increased market share (Ferrier, 2001). Lastly employee autonomy reflects the level of freedom employees have, to endeavour in entrepreneurial initiatives (Lumpkin et al., 2009). Because entrepreneurial firms rely on individual performances for the strategy to be successful, they often adopt a reward philosophy (Brown et al., 2001). The rewards philosophy means that teams or individual employees get formal rewards when they reach preset KPIs. The rewards philosophy provides incentives for employees to act proactively, increase the willingness to take risks and motivate to search for valuable new innovations. The individual effort maximalization results accumulated to better overall business performance for entrepreneurial firms (Bradley et al., 2011)

There has been a lot of research on the relationship between EO and business performance. Early results showed that firms with a high level of EO performed much better than firms without (Hult et al., 2003; Wiklund & Shepherd, 2003). The problem with these results were that they were over reliant on cross-sectional data and often included survival bias (Lomberg et al., 2017; Rauch et al., 2009; Schweiger et al., 2019). Recent results show that EO creates high variance in business performance (Patel et al., 2015) and positively influences firm failure too (Wiklund & Shepherd, 2011).

Resource Exhaustion Theory

The Resource Exhaustion Theory (RET) from Gali et al. (2023) states that every firm has entrepreneurial entropy (EE). EE is a measure for the level of resources exhaustion due to insufficient returns on investments in business activities. The EE level significantly increases when a business has a very high level of EO, when they have a high level of EO for a very long time or when they have an abrupt change in their EO level. An EO strategy increases the EE due to the tendency of prioritizing the exploration of business opportunities over the exploitation of these opportunities. The firm engages in a lot of promising projects but lacks in generating the necessary returns. High levels of EE are not sustainable because all resources will be exhausted, increasing the chance of firm failure. The most relevant finding in Gali et al. (2023) is that an abrupt change in the EO level increases the chance on bankruptcy significantly, especially if the business was already underperforming. This is because when top-management decides to abruptly change the EO level, the firm has no routines or business processes in line with the new strategy. Employees are therefore forced to quickly adapt to the new expectations, changing their work habits and behaviours. This adaptation process requires a lot of resources like time and training sessions, increasing the EE. That is why an abrupt change in EO for a firm that was already underperforming is especially dangerous. Whether the underperforming firm initially had a high or low level of EO, an abrupt change will require a lot of resources that are already scarce. In general, Gali et al. (2023) emphasize the fact that EO is a risky strategy and should therefore never be used as a solution and only as a strategy for expansion. A visual sketch of the authors interpretation of the ideal EO-cycle is included in appendix A.

The RET is constructed for the relationship between EO and business performance, but there are some connections with EH. Just like all resources can human resources be exhausted too (Conway et al., 2016). Exhaustion of human resources could burnout employees affecting their mental and physical well-being. Furthermore, the RET states that when the EO level of a company changes abruptly, employees have to change their work approach and behaviour. This means that job demands will change significantly, while it is uncertain whether job resources will match these changes. Ideally, the firm invests heavily to support their employees throughout the adaptation process. But, the abrupt change often requires other significant investments too, meaning that employees often receive insufficient support. The abruptness of the change therefore risks over-exploiting employees. The imbalance between job demands and resources could reduce job satisfaction (Bakker & Demerouti, 2014). The change in job demands and the need to adapt under time pressure may stress employees and affect their well-being (Schaufeli & Bakker, 2004). Additionally, the new job demands and expected work behaviour may not match employees' preferences, leading to a decrease in work engagement (Schaufeli & Bakker, 2004).

The role of firm size

There are a lot of factors that could influence the relationship between EO and EH, one of them being the firm size. Because EO has to spread throughout the organization to be successful (Hornsby et al., 2013; W. Wales et al., 2011), it might be a lot more difficult to reach all employees in bigger firms. In organizations with a lot of employees, top-management often struggles for alignment between different teams and hierarchy levels on the approach of the business strategy (Harvard Business School, 2018). Although autonomy is one of the EO dimensions, autonomy could become problematic when project teams become disconnected. This could affect the social connections and interactions between employees. In contrast, smaller firms have less hierarchy levels, meaning employees are closer connected to each other and to top-management. The closer connection with top-management could help employees to feel more comfortable with their autonomy due to the EO strategy (Griffin et al., 2001). Firm size can be beneficial too. Bigger firms generally have more resources available, making the chance on resource exhaustion smaller (Gali et al., 2023). Bigger firms could offer more job resources per employee or decrease the job demands by using more human resources to achieve the same goals. This will balance the job demands and resources to prevent negative effects on well-being. Furthermore, bigger firms often have more knowledge on how to capitalize on opportunities due to past experiences, increasing the chance of a successful EO strategy execution (Eshima & Anderson, 2017).

The fact that employees are closer connected in smaller firms might be extra important when the EO level abruptly changes. An abrupt change in the EO level will make an impact companywide due to the switch in job demands. Although employees might want to change their work behaviours, they are often unsure what the new requirements for the new job demands are. This uncertainty and confusion about new expectations or task prioritisation due to lack of experience is called role ambiguity (Andersén, 2017; Monsen & Wayne Boss, 2009). When employees experience role ambiguity it heavily affects their happiness as the uncertainty decreases their engagement. In smaller firms where employees are better connected, they can help each other to solve this role ambiguity, by talking to each other and explaining the changes and developments. In bigger firms, role ambiguity might be more present. The abrupt switch in EO has to spread through all levels of the organization, from top to bottom, layer by layer. At every level some uncertainty about the new strategy remains. The accumulating role ambiguity reaches its maximum for the lowest level employees.

2.2 Hypotheses construction

Entrepreneurial Orientation and Employee Happiness

Looking at the overlap between the EO and EH constructs, the first match for employee autonomy is evident. EO prioritizing autonomy for employees gives them freedom and decision making power that will make them feel valued and respected, increasing work engagement and job satisfaction (Deci & Ryan, 2000; Lumpkin et al., 2009). Another connection is that proactiveness and risk-taking will lead to new business opportunities that will offer learning and growth opportunities (Noe et al., 2014; Sitkin et al., 1992). When employees feel like they are learning and developing, they are more engaged and motivated to perform. Furthermore, with EO's emphasis on innovation, the work environment and culture is often supportive and inclusive (Damanpour & Schneider, 2006). This will increase the mental and physical well-being of employees and lead to greater job satisfaction (Hurley & Hult, 1998; Judge & Klinger, 2008). Lastly, the rewards philosophy often used by entrepreneurial firms incentivizes employees to get the most out of themselves. This drive initially increases the job demands, but has a positive effect on work engagement and job satisfaction when the KPI's are achieved (Gupta & Shaw, 2014).

The JD-R (Bakker & Demerouti, 2014) states that there should be a healthy balance between job resources and job demands for employees to be happy. Although an EO strategy often requires higher job demands due to the need for innovation, proactive behaviour and the ability to work under uncertainty, it provides additional job resources too. The reward philosophy, supportive environment and substantial amount of individual development opportunities provides the balance needed for high EH. The first hypothesis therefore states:

Hypothesis 1:
"Entrepreneurial Orientation has a positive effect on Employee Happiness"

Abrupt change in Entrepreneurial Orientation and Employee Happiness

Due to an abrupt change in the level of EO, the EE increases. When a firm has a high level of EE it uses a lot of resources for the execution of risky projects with insufficient returns, risking exhaustion of their resources. It is easy to measure to which extent tangible resources like cash or stock are exhausted, but human resources can be exhausted too. When a firm abruptly changes their level of EO, employees are required to quickly adapt their work behaviour. Their job demands change while the job resources often do not match the employees' new needs. This imbalance could lead to the exhaustion of human resources, affecting the job satisfaction and well-being of employees. Additionally, the abrupt switch could mean that the individual and company values are not aligned anymore from an employee perspective. When individual and company values are not aligned anymore, employees will have less engagement to their job.

Overall, an abrupt change in the EO level does seem to risk EH. The chance on human resource exhaustion, the increase in job demands with uncertain new job resources and switch in company values could affect EH negatively. This results in the second hypothesis:

Hypothesis 2:
"An abrupt change in the level Entrepreneurial Orientation has a negative effect on Employee Happiness"

Moderating effect of firm size

Smaller firms are more agile and employees are better connected. Top-management is closer connected to the employees as well, as there exist less hierarchy levels. It is therefore easier for the

EO strategy to spread throughout the company and create alignment for the approach and execution. Employees will feel more comfortable with their autonomy and responsibility when they can get support from colleagues or top-management when needed. Although bigger firms have more resources available to support employees during the EO strategy, this does not seem to outweigh the potential stress originating from EO. Especially when the level of EO abruptly changes. The immediate switch in job demands resulting in role ambiguity could strongly affect the EH. With the role ambiguity increasing at every hierarchy level, abrupt changes might even paralyze parts of the firm. As the different teams at the same hierarchy level are less connected in big firms, it is more difficult to clear this role ambiguity. The third and fourth hypotheses are therefore:

Hypothesis 3:
"The number of employees mitigates the positive effect of Entrepreneurial Orientation on Employee Happiness"

Hypothesis 4:
"The number of Employees amplifies the negative effect of an abrupt change in the level of Entrepreneurial Orientation on Employee Happiness"

3. Methodology

This chapter contains the description of the quantitative research approach. With a deductive approach the hypotheses from the previous chapter will be tested. First, the available data and its origin will be described and discussed. This will be followed by the operationalization of the variables and the construction of the database that will be used for the analysis. Next, the variable descriptives and correlations will be analysed. This chapter will end with the analytical approach and statistical test that will be performed to create relevant results.

3.1 Data description

The data used in this research originates from two sources. The first source is a panel dataset of the S&P 500 (S&P Global, 2024) companies during 2016-2020, provided by J.P. Coen Rigtering. This dataset consists of 2505 entries, with 5 entry years for 501 companies. The S&P 500 is a stock market index of 500 of the largest public companies in the United States. These companies together represent approximately 80% of the total market capitalization of the U.S. public companies. These companies are active in different industries, have different financing structures and vary heavily in their number of employees. The S&P 500 is a fitting sample for this research as they are the key drivers of global economics, while possessing unique characteristics and traits. Additionally, the fact that they are public listed companies means that verified data is publicly available. The second source is a database originating from Compustat, provided by Wharton Research Data Services (Wharton Research Data Services, 2024). The databases could be merged based on the individual company ticker and year of each entry.

S&P 500 database

The S&P 500 panel database consist of 4 distinct parts. The first part contains the name and year of each entry as well as the general company information like the founding date, company sector and industry. For the second part of the database the shareholder letters were individually analysed with computer aided text analysis (CATA) (Short et al., 2010). CATA is a digital technique to analyse texts and papers. The idea is that predefined words, its synonyms and similar phrases are counted throughout the text. This way the sentiment and topic of the text can be measured without the need of reading everything. The results from CATA showed how many times each of the 5 dimensions of entrepreneurial orientation were mentioned in that year's shareholder letter. The number of times each of the 5 dimensions were mentioned got summed and divided by the total number of words in the shareholder letter. This represents the average level of EO for the company that year. The third part of the database consists of review ratings from Indeed (Indeed.com, 2023). The database contains average review ratings per company per year, and scores for different components of employee happiness. The average review ratings follow the longitudinal format of the rest the dataset, but the different employee happiness components are cross-sectional per company. This data was assembled by web scraping the Indeed review pages of the individual companies. Each individual review contains an overall score and a date (appendix B1). The scores for each of the components of employee happiness are not tracked per year. That is why this data is only available in the cross-sectional format. The fourth and final part of the S&P 500 dataset contains yearly financial data for all of the companies. More than 100 financial figures like total assets, EBITDA, stock price and shares outstanding are web scraped from MacroTrends (macrotrends.net, 2023).

Compustat

Compustat is a database for financial, statistical and market information of companies all over the world. In 1962 the database was started and it includes all companies of the S&P 500 too. To test hypothesis 3 and 4, the number of employees were required. These were provided by Wharton Research Data Services, including the company ticker and year. Based on the year and the company ticker, the databases could be merged to one database that included all necessary variables.

3.2 Variable and database construction

This section starts with an explanation on how the concepts from the theoretical background are turned into measurable variables and how these variables have been constructed. This will be followed by the construction of the final database. The section will end with the descriptive statistics and correlation matrix.

Measures

Dependent variable: The construct *employee happiness* is the dependent variable and is represented by the average review rating the company has had in that year on Indeed. Although individual EH is a multi-dimensional construct, it is analysed as a firm level characteristic in this paper. Because the average review rating is publicly available, it is an important influence on the public opinion about the company. As not just the employees hired via Indeed, but all employees are able to leave a review, the Indeed score acts as soft check for the employers to take care of their employee's happiness. When a company has a negative average review rating, this will not only repel future job seekers, but also investors, clients and potential partners. This makes the average review rating on Indeed a valid representation of the employee happiness at the company.

Each individual Indeed review contains a 1-5 rating, the date the rating was given, if the person is still working at the company and a short text to explain the rating. The review rating can only be a full integer, so a single review cannot have a rating of 3,5 for example. For each firm in the S&P500, the ratings and dates of all the reviews from 2016 till the end of 2020 were web scraped. Per year, the scores were summed and divided by the total numbers of reviews of the frim, giving the average review rating for the company that year. In order for the employee happiness rating to be valid, the firm needed to have a least 15 reviews that year. This threshold was set to prevent overreliance on individual experiences. Both current and former employees are able to leave a review. The reviews of former employees could include some bias as they are not working there anymore. A thorough explanation of the Indeed platform is given in appendix B1.

Independent variables: For *entrepreneurial orientation* the percentage of words related to the EO-dimensions in shareholder letters has been used. This percentage calculated with CATA represents the level of EO top-management wants to pursue. Although Short et al. already proposed this technique in 2010, most studies use financial measures to construct the level of EO (Gali et al., 2023; Kreiser et al., 2020). Because this study focusses on the effect of the level of EO on employees, the construction of EO via CATA on shareholder letters is a good representation. This reflects the top-management style and strategy, which will directly affect the employees.

The abrupt change in the level of EO was calculated as the absolute difference between the predicted change in EO and the actual change in EO. Before finding the predicted change in EO, the expected levels of EO needed to be estimated. This was done with a linear regression estimation using the following formula:

$$EO_t = \alpha + \beta_1 * Year_t + \beta_2 * EO_{t_{-1}} + \sum_{i=1}^{n-1} \gamma_i * Firm_i + e_t$$

The predicted level of EO was estimated with the use of the time variable, the level of EO of the previous year, firm fixed effects and the error term. The time variable was used to account for general developments in EO between 2016 and 2020. By including a lag variable, the expected EO level was dependent on the firms EO level of the previous year. With the firm fixed effects, the company specific factors were included. The error term accounts for all the unexplained variation left for EO. By subtracting the EO level of the previous year from the expected EO level, the expected change in EO remained. The last step to find the abrupt change in the level of EO was to find the absolute difference between the expected and actual change in EO level. This value shows how much the actual change in EO varied from the trend. The higher the value, the more drastic the change in EO level is. The absolute value is used because in this study it is not relevant whether the level of EO increased or decreased, just that it abruptly changed. As the abrupt change is relative to the EO level of the year before, the values could not be calculated for the first year in the database. The value of abruptness of change in the level of EO for all entries in 2016 are therefore zero.

Firm size is reflected as the firm's total number of employees divided by a thousand. These were provided by WRDS and controlled via Stock Analysis (stockanalysis.com, 2024). The reason why they were divided by a thousand is that it makes it easier to read, without losing any of the information. The number of employees is often logged to account for potential issues with heteroskedasticity (Gali et al., 2023). But, the results of a logged variable shows the impact of percentual change. This was not done in this study because it wants to find the direct effect of an increase in the number of employees.

Moderators: Hypotheses 3 and 4 expect the number of employees to act as a moderator for the effect of EO on EH and an abrupt change in EO on EH. A moderator is constructed by multiplying two independent variables. The goal of the moderator is to prove that the combination of these independent variables significantly impacts the dependent variable. To minimize multicollinearity the independent variables are mean centred before the multiplication. When a variable is mean centred, a variable's average get subtracted from each individual score, turning the mean to zero.

Control variables: The control variables are based on the control variables of Gali et al. (2023), with those selected, possibly affecting EH. The first control variable is *firm age*, calculated by subtracting the founding year from the entry year. Because the relationship between EO and firm growth is stronger in younger firms (Anderson & Eshima, 2013), it could affect the relationship between EO and EH as well. Some of the companies had several founding dates due to mergers or rebranding. Each of these cases were individually assessed and the most logical option was chosen. The second control variable is the *Industry group adjusted Tobin's Q*. Tobin's Q is the ratio between the valuation of the firm and the total value of its assets. Although a high Tobin's Q can influence the chance of firm failure (Opler & Titman, 1994) it is also a measure for firm performance (Singh et al., 2018). When two firms with similar assets are valued differently, the higher valued firm is doing better due public opinion. The higher valuation can give access to new business opportunities. But, if the valuation suddenly plummets, the firm could face severe consequences it might not be able to handle. The overvaluation can therefore both increase employee happiness because they are proud to work at the firm, or decrease EH as the valuation is mostly based on hype. To adjust the Tobin's Q, the industry group average was subtracted from it. The calculations for the industry adjusted Tobin's Q are shown in Appendix B2. As firms with better financial business performance have more resources to invest in their employees (Mahssouni et al., 2022), three financial control variables are included.

Free cash flow, represented by the EBITDA of the firm, shows how much money the business is generating that could be reinvested. *Financial Leverage* measured by the debt-to-equity ratio reflects the firm's finance structure and financial flexibility. *Resource Slack* is calculated by dividing total current assets over total current liabilities. This shows how much resources are available to invest in new projects or strategies. The final control variable is a dummy for 2020. In 2020, the virus COVID-19 spread all over the world. It affected citizens in their daily life, and the government forced companies to take measures. In a lot of sectors it was mandatory to work from home, reducing connection and relationships with colleagues and supervisors. COVID-19 could therefore be an external factor affecting employee happiness (Mehta, 2021).

Database construction

After the construction of all the variables a lot of entries needed to be removed. This is because a lot of entries had incomplete data. Because the independent variable the abruptness of change in EO is time and firm dependent, the decision was made to erase all the firms that did not meet the complete records requirement. For 805 entries there was no shareholder letter analysed, resulting in the absence of an EO-score. 85 entries missed the necessary data for the construction of the Tobin's Q. There were 203 entries without a review score, and an additional 152 entries that did not meet the minimal number of review threshold of 15. Finally, 220 entries needed to be deleted to fulfil the complete records requirement. This resulted in 1040 entries for 208 firms. One problem that remained was that the EBITDA generated by banks via financial services is publicly available. These bank did fulfil the complete records requirement other than the EBITDA variable. Because the industrial EBITDA of banks is available to the public, this was used to prevent the exclusion of more entries.

Descriptives and Correlations

Table 1, 2 and 3 on page 15 provide information about the included variables. Table 1 presents the main descriptive statistics, table 2 shows the yearly averages for the dependent and independent variables and table 3 contains the correlation matrix for all the variables included.

Descriptives

The employee happiness scores are relatively high, averaging 3,661 out of 5 with a low standard deviation of 0,349. Interestingly, employee happiness decreases almost linearly each year. The variations indicate that happiness levels differ slightly more between firms than within firms over time. The mean of EO is 0,032, meaning that on average 3,2% of words in shareholder letters are EO-related. The abruptness of change in EO has an even lower mean. This is because in 2016, the abruptness of change was zero for all firms, leading to a lower mean than the standard deviation. Notably, the value for abruptness more than doubles from the 95th percentile to the maximum value. Table 2 shows that firms were already changing their EO strategy in 2019, but the average level of EO dropped heavily in 2020. Although employees are becoming less happy every year, the average number of employees keeps increasing every year. A plausible explanation is that the total number of people eligible to work in the US is increasing every year (Statista, 2024). The number of employees varies significantly between firms, resulting in a high standard deviation compared to the overall mean. The difference between the 95th percentile and the maximum value indicates that a few firms are much larger than the others. The 5th and 95th percentile of EBITDA and debt-to-equity ratio also indicate the presence of heavy outliers. Interestingly, the debt-to-equity ratio has higher within variation than between variation, even though it is a firm specific metric. This is probably because the ratio heavily changes when a firm gets a new loan. The major difference between the within and between variation for firm age is due to the way it is operationalized. Every year the firm age increases by one year, while the firms all have different founding dates. Logically, the COVID-19 dummy has a between variation of zero because it is similar for all firms and a within variation of 0,2 because the dataset consists of 5 years.

Correlations

Employee happiness significantly correlates with the level of EO, the abruptness of change in EO, EBITDA and the COVID-19 dummy. The level of EO is positively correlated with employee happiness while the abruptness of change is negatively correlated. This suggests that employees are happier in entrepreneurial firms, while employees are less happy when the level of EO abruptly changes. The positive correlation with EBITDA indicates a connection between employee happiness and the amount of cash a firm generates. The dummy variable for 2020 has interesting significant correlations. It is negatively correlated with employee happiness, suggesting that consequences of COVID-19 indeed decreased employee happiness. The yearly average of employee happiness is indeed the lowest in 2020, but follows the trend throughout the years. Furthermore, 2020 is negatively correlated with the level of EO but positive with the abruptness of the change in EO. This implies that companies abruptly lowered their EO level due to the rise of COVID-19, which is in line with the yearly averages. A significant negative correlation between the level of EO and the number of employees suggest that bigger firms are less entrepreneurial. The positive correlation between the level of EO and resource slack was not expected. Following the resource exhaustion theory, EO contributes to high level of EE, meaning that resources are getting exhausted. The positive correlation implies that a high level of EO is associated with high resource availability. Overall, the correlations between the included variables are weak or very weak. Because of the low correlations, some problems might arise in the estimation of the regression models. The one exception is the correlation between the number of employees and EBITDA. This correlation does make sense as bigger companies usually have more revenue and thus often more free flowing cash.

3.3 Analytical approach

The hypotheses will be tested with a linear regression model. This linear regression model can be constructed with various estimation methods. The estimation methods included in this study are first differences (FD), fixed effects (FE) and random effects (RE). Each of these estimation methods account for the longitudinal characteristics of the panel dataset. With FD estimation, for each variable the value of moment *t-1* is subtracted from the value at *t* to account for possible heterogeneity problems, at the cost of losing the first time period. FE and RE do not require the loss of the first period. In the FE model firm fixed effects are included in the regression analysis. The firm fixed effects account for unobserved heterogeneity that varies across entities but is constant over time. By including firm fixed effects the risk on omitted variable bias in reduced, as it accounts for firm specific factors that could affect the results. In contrast, in RE estimation unobserved firm specific parameters are treated as random variables instead of fixed parameters. Each of these three models require strict exogeneity to generate significant results. This means that the error term of the regression model does not correlate with any of the explanatory variables. For the RE model to generate significant results, the explanatory variables are not allowed to correlate with the constant. Otherwise the firm specific parameters are not treated as random.

The first model that will get estimated is the FD model. After the estimation, the model needs to be tested on autocorrelation with the Breusch-Godfrey test. If the lagged predicted residual parameter is -0,5 the model will be re-estimated with clustered standard errors. The second model is the FE model and these results are tested on autocorrelation with the Durbin-Watson test. This test results in a value between 0 and 4. If the value is close 2 there is no autocorrelation suspected. When the Durbin-Watson value is close to 0, positive autocorrelation is suspected and with a value close to

4, negative autocorrelation is suspected. If autocorrelation is suspected, the model is re-estimated with robust standard errors. The last models will be estimated with RE estimators. Just like with FE, the Durbin-Watson test shows if robust standard errors are needed.

When all models are estimated, they need to be compared to identify the most suitable model to test the hypotheses. First need to be determinded if FD or FE is preferred. Based on the pattern of the residuals of the FE model, the preferred model is chosen. FD is preferred when the residuals follow a random-walk, FE is preferred if the residuals show a white noise pattern. If the FD estimates are preferred, these models will be used to test the hypotheses. If the FE estimates are preferred, the Hausman-test is performed to see if RE is preferred over FE. The null hypothesis states that RE is preferred and the alternative hypothesis that FE is preferred. When the Hausman-test yields a significant result, FE is the most preferred estimation method.

For each estimation method, 7 models will be constructed. The first model consists of just the dependent variable and the control variables, functioning as the baseline. In each of the subsequent models additional explanatory variables are added to see how they change the model. This way the individual impact of added variables can be closely examined, with model 7 including all variables. An overview of the variables included in each model is shown in appendix B3. For the comparisons and statistical test between the different estimation methods, all models are taken into consideration.

Once the preferred models are determined, some additional tests need to be performed. The first test is the Breusch-Pagan test for heteroskedasticity. Heteroskedasticity means that the variance of the residuals is not constant over time. The standard errors might therefore be biased, making the coefficients unreliable to test the hypotheses because the T-test results change. The null hypothesis for the Breusch-Pagan test is that homoscedasticity and the alternative hypothesis heteroskedasticity. If the p-value of the BP-test is lower than 0,05 the null hypothesis is rejected, implying that the model contains heteroskedasticity. To solve this, robust standard errors are needed.

The second test is the Shapiro-Wilk test for normality of the residuals. This is often combined with an histogram and Q-Q plot because a the Shapiro-Wilk test only tests if the residuals are normally distributed. In case of a little deviation from the normal distribution, the Shapiro-Wilk test yields very strong results, while the graphs might be more forgiving. If the residuals are normally distributed, the estimated parameters are efficient and viable for testing the hypotheses. The null hypothesis is that the residuals are normally distributed, and the alternative hypothesis that they are not. A p-value lower than 0,05 rejects the null hypothesis, implying that the residuals are not normally distributed.

The final test on the preferred model is the test for multicollinearity. In a regression model, each variable has a VIF-score. This VIF-score reflects how strong that variable is correlating with the other variables included in the model. When the variable has a VIF-statistic of 10 or higher, this indicates multicollinearity. The exception is that a high VIF-score for the intercept usually can be ignored.

Once the preferred estimation method is identified, various robustness tests will be performed. The explanatory variables will be changed and time fixed effects estimation will be tested. Only model 7 will be used for these robustness tests because it includes all variables. Because of the linear decrease in employee happiness (table 2), model 7 will once be estimated without the COVID-19 dummy and once with time fixed effects instead of firm fixed effects. This way the role of the decreasing employee happiness in the data can be identified. The other robustness tests are estimation without control variables, estimation without 2016, estimation when all the variables are log-transformed and estimation with the exclusion of all outliers.

After the statistical and robustness tests, the hypotheses will be tested. The hypotheses will be tested with the main models. Combining overall models statistics, variable parameters and significance levels, the hypotheses will either be confirmed or rejected. The results from the robustness tests could function as additional context in testing the hypotheses. With margin plots the effect of the moderators on the dependent variables will be visualized. Margin plots shows the effect of an explanatory variable on the dependent variable and the 95% confidence interval surrounding the specific value of the moderator.

Table 1: Descriptive Statistics

				Percentile			*Variation*	
Variable	Mean	SD	Min	5%	95%	Max	Within	Between
1. Employee Happiness	3,661	0,349	2,225	3,037	4,149	4,696	0,050	0,082
2. Level of EO	0,032	0,010	0,00	0,016	0,048	0,060	5,512E-05	5,412E-05
3. Abruptness change EO	0,00378	0,00427	0,00	0	0,0121	0,0297	1,500E-05	6,222E-06
4. Number of employees (*1000)	67,379	105,427	1,621	4,63	291,08	1298	735,48	10566,7
5. acEO*EMP	-0,006	0,440	-2,565	-0,666	0,241	6,231	0,147	0,076
6. EO*EMP	-0,073	0,995	-10,110	-1,356	0,976	5,845	0,562	0,542
7. Adjusted Tobin's Q	0,357	1,351	-2,716	-1,274	2,559	10,777	0,560	1,382
8. Resource Slack	1,438	0,897	0,070	0,398	2,919	7,253	0,148	0,688
9. Firm age	83,168	49,737	1	19	171	236	2,5	2481,27
10. Debt-to-Equity Ratio	1,591	12,836	-59,685	0,064	4,866	384,294	147,21	47,07
11. EBITDA (M$)	6086,420	11897,235	-10478,00	492,92	24069,70	192250,00	3,52E+07	1,14E+08
12. Dummy 2020 (COVID-19)	0,2	0,4002	0	0	1	1	0,2	0

N = 1040, Number of firms = 208,

EO = Entrepreneurial Orientation; acEO = Abruptness change EO

Table 2: Averages per year

Year	EH	EO	acEO	Number of employees (*1000)
2016	3,844	0,0322	0,0000	62,47
2017	3,775	0,0318	0,0224	64,91
2018	3,683	0,0332	0,0188	67,61
2019	3,545	0,0319	0,0272	68,88
2020	3,461	0,0296	0,0297	73,03

N = 1040, Number of firms = 208,

EO = Entrepreneurial Orientation; acEO = Abruptness change EO

Table 3: Correlations matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Employee Happiness	-											
2. Level of EO	0,120**	-										
3. Abruptness change EO	-0,115**	-0,059	-									
4. Number of employees (*1000)	0,048	-0,070*	-0,014	-								
5. acEO*EMP	0,006	0,039	-0,017	-0,050	-							
6. EO*EMP	-0,032	0,002	0,040	-0,279**	0,005	-						
7. Adjusted Tobin's Q	-0,044	0,059	0,056	-0,016	-0,047	-0,013	-					
8. Resource Slack	-0,019	0,096**	0,017	-0,120**	0,005	0,051	0,238**	-				
9. Firm age	0,041	0,021	-0,114**	0,004	0,032	0,033	-0,124**	-0,219**	-			
10. Debt-to-Equity Ratio	0,036	0,006	-0,022	0,031	0,011	0,007	-0,056	-0,026	0,095**	-		
11. EBITDA (M$)	0,178**	-0,057	-0,063*	0,463**	-0,143**	-0,273**	-0,045	-0,116**	0,089**	0,006	-	
12. Dummy 2020 (COVID-19)	-0,288**	-0,108**	0,119**	0,027	-0,070*	0,016	0,054	0,01	0,02	0,006	0,006	-

*N = 1040, Number of firms = 208, Pearson correlation coefficients in the lower left diagonal, *p<0,05, **p<0,01*

EO = Entrepreneurial Orientation; acEO = Abruptness change EO; SD= standard deviation

4. Results

4.1 Preferred model identification

Following the analytical approach, the different estimation methods were executed to find the most suitable regression estimation method. The regression models were calculated in Python (Van Rossum & Drake Jr, 1995). The codes that were written for the data analysis can be found in Appendix C1. The first difference models were estimated first, including the Breusch-Godfrey test. The Breusch-Godfrey test showed that the lagged residuals were very significant in all models (p=0,002), strongly suggesting the presence of autocorrelation. The FD-models were therefore estimated again, this time with clustered standard errors. Next, both the fixed effects and random effects models were estimated. In the estimation process of these models, several variables got fully absorbed due to the inclusion of firm age. Therefore, firm age was excluded as a control variable. Both the FE and RE models were tested on autocorrelation with the Durbin-Watson test. The Durbin-Watson statistics for both FE and RE are shown in table 4 underneath.

Table 4: Durbin-Watson test

		DW-statistic
Fixed effects	Model 1	1,908
	Model 2	1,909
	Model 3	1,958
	Model 4	1,958
	Model 5	1,960
	Model 6	1,958
	Model 7	1,960
Random effects	Model 1	1,602
	Model 2	1,594
	Model 3	1,635
	Model 4	1,635
	Model 5	1,636
	Model 6	1,625
	Model 7	1,636

As both scores are quite close to the value 2, there is no autocorrelation suspected. This means that there is no need for robust standard errors. Next, the pattern of the residuals of the FE models were analysed. The residuals of each model show a white noise pattern (appendix C2.1), meaning that FE estimation is preferred over FD. As FE is preferred over FD, the Hausman-test should be performed to see if RE or FE yield better results. Table 5 shows the Hausman-scores and p-values for each model.

Table 5: Hausman test

	Score	p-value
Model 1	23,31	0,001
Model 2	37,28	0,000
Model 3	42,67	0,000
Model 4	44,73	0,000
Model 5	45,91	0,000
Model 6	45,68	0,000
Model 7	46,91	0,000

Based on these very significant results, the fixed effects model is preferred over the random effects model. To see if the fixed effects model is suitable to test the hypotheses, four more tests need to be performed. First, the model is tested on heteroskedasticity with the Breusch-Pagan test. Table 6 shows that all the models test positive for heteroskedasticity. To solve this, the model will be estimated with robust standard errors.

Table 6: Breusch-Pagan test - FE

	Score	p-value
Model 1	16,28	0,006
Model 2	16,63	0,011
Model 3	25,34	0,001
Model 4	34,92	0,000
Model 5	36,00	0,000
Model 6	35,20	0,000
Model 7	36,35	0,000

Now the endogeneity assumption for fixed effects needs to be confirmed. This is done by regressing the residuals over the explanatory variables. The results show that all explanatory variables are completely insignificant in all models, meaning that the endogeneity assumption is met. With the Shapiro-Wilk test is checked if the residuals are normally distributed. Table 7 shows that the p-values for the Shapiro-Wilk test are very low, indicating that the residuals are not normally distributed.

Table 7: Shapiro-Wilk test - FE

	Score	p-value
Model 1	0,994	0,001
Model 2	0,994	0,001
Model 3	0,994	0,000
Model 4	0,994	0,000
Model 5	0,994	0,000
Model 6	0,994	0,000
Model 7	0,994	0,000

Because of these significant results, the normality of the residuals is further investigated with residuals histograms and Q-Q plots. These graphs are presented in appendix C2.2. The histograms show that the residuals are strongly normally distributed. Looking at the Q-Q plots, the residuals mostly follow the normally distributed red line, but deviate from the line in the highest and lowest theoretical quantiles. This tail behaviour suggest some skewness or kurtosis in the residuals. Although this is not ideal in databases with less than 10 entries per individual firm (Schmidt & Finan, 2018), the violation of the normality assumption is accepted in this study because of the histogram and Q-Q plots. The last test is on multicollinearity, for which the VIF-scores need to be calculated. Table 8 shows the VIF-scores for all variables in the different models. The VIF-scores indicate that there is no suspicion for multicollinearity. Only the VIF-scores of the constants of model 2 to 7 are above the threshold of 10. But a high VIF-score for the constant is not unusual and generally not problematic (Salmerón-Gómez et al., 2024).

Table 8: VIF-scores for multicollinearity - FE

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	4,336	14,444	15,520	15,991	16,018	15,992	16,018
Adjusted Tobin's Q	1,066	1,068	1,071	1,071	1,072	1,074	1,075
Resource Slack	1,073	1,080	1,080	1,086	1,086	1,086	1,086
Debt-to-Equity Ratio	1,003	1,004	1,004	1,005	1,005	1,005	1,005
EBITDA (M$)	1,014	1,016	1,020	1,285	1,322	1,310	1,349
Dummy 2020 (COVID-19)	1,003	1,016	1,028	1,029	1,029	1,033	1,033
Level of EO	X	1,026	1,029	1,031	1,031	1,031	1,032
Abruptness change EO	X	X	1,024	1,024	1,025	1,025	1,025
Number of employees (*1000)	X	X	X	1,285	1,327	1,285	1,328
acEO*EMP	X	X	X	X	1,119	X	1,120
EO*EMP	X	X	X	X	X	1,030	1,031

EO = Entrepreneurial Orientation; acEO = Abruptness change EO

Following the results from all the statistical tests above, the fixed effects models with robust standard errors are most suitable model to test the hypotheses. The model is still not optimal, as the Shapiro-Wilk test yielded very significant results. Nevertheless, the models do fulfil the endogeneity requirements and the histograms and Q-Q plots show that the residuals are generally normally distributed. The results of the linear regression models are shown in table 9.

Table 9: Regression result - Fixed effects

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6		Model 7	
	Coefficient	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**
Intercept	3,6735**	0,0264	3,7019**	0,0401	3,7572**	0,0401	3,7617**	0,0414	3,7612**	0,0408	3,7614**	0,0415	3,7610**	0,0409
Adjusted Tobin's Q	-0,0224*	0,0088	-0,0229**	0,0088	-0,0192*	0,0087	-0,0192*	0,0087	-0,0198*	0,0087	-0,0191*	0,0087	-0,0198*	0,0087
Resource Slack	0,0381*	0,0175	0,0376*	0,0176	0,0292	0,0170	0,0291	0,0171	0,0289	0,0170	0,0290	0,0171	0,0289	0,0170
Debt-to-Equity Ratio	-0,0003	0,0003	-0,0003	0,0003	-0,0003	0,0003	-0,0003	0,0003	-0,0003	0,0003	-0,0003	0,0003	-0,0003	0,0003
EBITDA (M$)	-1,444E-06	7,878E-07	-1,419E-06	7,789E-07	-1,2576E-06	7,132E-07	-1,199E-06	7,089E-07	-1,231E-06	7,213E-07	-1,202E-06	7,099E-07	-1,233E-06	7,219E-07
Dummy 2020 (COVID-19)	-0,2471**	0,0153	-0,2493**	0,0156	-0,2390**	0,0158	-0,2385**	0,0159	-0,2391**	0,0160	-0,2380**	0,0161	-0,2393**	0,0161
Level of EO	X	X	-0,8599	0,8777	-1,2442	0,8479	-1,2408	0,8485	-1,2491	0,8376	-1,2349	0,8477	-1,2452	0,8378
Abruptness change EO	X	X	X	X	-9,3713**	1,6984	-9,3591**	1,6996	-9,4597**	1,6829	-9,3645**	1,6933	-9,4625**	1,6794
Number of employees (*1000)	X	X	X	X	X	X	-0,0001	0,0002	0,0000	0,0002	-0,0001	0,0002	0,0000	0,0002
EO*EMP	X	X	X	X	X	X	X	X	0,0132*	0,0060	X	X	0,0131*	0,0060
acEO*EMP	X	X	X	X	X	X	X	X	X	X	-0,0046	0,0127	-0,0030	0,0126
R-squared	0,2597		0,2605		0,2855		0,2856		0,2875		0,2856		0,2875	
R-squared (Between)	-0,0550		-0,0615		-0,0579		-0,0624		-0,0676		-0,0617		-0,0671	
R-squared (Within)	0,2597		0,2605		0,2855		0,2856		0,2875		0,2856		0,2875	
R-squared (Overall)	0,0495		0,0454		0,0561		0,0532		0,0503		0,0536		0,0506	

*Firm fixed effects included; *p<0,05, **p<0,01*

Number of observations = 1040, Interaction terms are mean-centered

EO = Entrepreneurial Orientation; acEO = Abruptness change EO; S.E.= standard error

4.2 Model results

Table 9 contains the results for the regression models estimated with fixed effects using robust standard errors. The first thing that stands out are the negative values for the R-squared between. This indicates that the model is not suited to predict the differences between firms. The R-squared within is considerably, meaning that the model can predict changes in employee happiness within firms. The overall R-squared for each of the 7 models is around 0,05 which means that about 5% of the employee happiness variance is explained by the models.

In each model the intercept is very significant. In model 1, three of the included control variables have a significant parameter. The dummy for 2020 is very significant (p-value<0,01) and shows that employee happiness dropped by 0,247 out of 5, due to the effects of COVID-19, which is in line with past findings (Mehta, 2021). The adjusted Tobin's Q and resource slack are also significant. Tobin's Q negative coefficient (-0,0224) means that employee happiness decreases if a firm is overvalued. The positive value for resource slack (0,0381) shows that employees are happier when their firm has more resources available to invest. Tobin's Q and the COVID-19 dummy yield similar results in the other models, but model 3 to 7 resource slack is not significant anymore. By the inclusion of the level of EO in model 2, the overall explained variance actually decreases. Additionally, the level of EO has an insignificant negative coefficient (-0,8599). This is very strange as the level of EO is significantly positive correlated with employee happiness (table 3). In contrast, the abruptness of change in EO does have a significant contribution in every model it is included in. It has a very significant (p-value<0,001) highly negative coefficient (-9,371). The reason the coefficient is so high is because the abruptness of change in EO has very small values, with the mean value only lowering the employee happiness by 0,035 out of 5. With the inclusion of the number of employees, the within variation remains similar, while the between variation becomes more negative. This further decreases the overall R-squared, with the coefficient for the number of employees not being significant in any of the models it is included. It is therefore remarkable that the first moderator, being the product of the level of EO and the number of employees does have a significant (p-value<0,05) positive coefficient (0,0132). This does align with the idea that larger companies have more resources and knowledge to make the EO strategy successful (Eshima & Anderson, 2017). But with the inclusion of this first moderator, the between variation yet again decreases. Although the within variation does slightly increase, the overall variation is still lower than in model 4. The correct interpretation of the positive coefficient seems therefore that the if a firm grows while having a EO strategy, it increases employee happiness. Model 6 contains the second moderator instead of the first, but the coefficient does not yield a significant result. In model 7 all variables are included. It has the highest within explained variance, but third worst overall explained variance.

4.3 Robustness Tests

Appendix C3.1.1 contains the results of all models that were estimated as robustness tests. All models were estimated with robust standard errors to account for heteroskedasticity. In all models except for the time fixed effects model, entity fixed effects are included. Looking at the first model, the exclusion of the COVID-19 dummy significantly decreases all R-squared values compared to the final model 7. Although the level of EO coefficient is still insignificant, it does change from negative to positive. This could be because the value of the intercept has dropped as the COVID-19 dummy was very significant with a negative coefficient. In the second model with time fixed effects instead of firm fixed effects, the results change completely. The intercept value is 0,2 lower, and instead of the abruptness of change in EO, the level of EO becomes very significant (p-value<0,01). The coefficient for the level of EO in this model is positive (3,647). The EBITDA coefficient has a positive ($6{,}461*10^{-6}$) significant (p-value<0,01) value too. The R-squared values are opposite to the values with firm fixed effects, which is expected as the time fixed effects accounts for variance across time instead of across entities. The time fixed effects R-squared values are problematic too, as the within variance has a negative value. However, the overall R-squared value is similar to the final fixed effects models. The fact that the abruptness of change in EO does becomes insignificant and turns positive, indicates that the significance of the abruptness of EO in the firm fixed effects models includes a lot of the employee happiness time trend (table 2). This is further confirmed in the third robustness model, where all 2016 entries are deleted. In this model the abruptness of change in EO becomes positive and insignificant too. As the abruptness of EO is an absolute value with all 2016 entries having value zero and employee happiness decreases every year, the significant relationship in the final models seems to be biased. None of these first three robustness test models has a significant coefficient for the number of employees.

In the fourth model, the control variables were excluded to see the explanatory power of the independent and moderating variables. The results show that coefficient of the variables stayed similar, only the coefficient for the number of employees becomes significant. This indicates that the number of employees is connected with employee happiness through one of the control variables. Without the control variables, the explained variance got a lot worse. The overall R-squared turned negative, indicating that the predictive quality of the model is worse than just using the mean of employee happiness. For the fifth and sixth robustness model, the included variables were modified. In the fifth model, all variables were log-transformed to make the variables more normally distributed. In the sixth model, all entries that contained an outlier for one or more of the variables were excluded. The outliers were estimated with the formula in appendix 3.1.2. With the variable modification the overall variance of both models turned negative, meaning that they are not suited to test the hypotheses.

The time fixed effects model has an overall R-squared value similar to the final fixed effects model. In Python, time fixed effects models can be estimated automatically by including it in the code, or manually by adding a dummy for every year except the reference year. The included year dummies explain a lot of both the within and between variance due to the time trend in employee happiness. This seemed promising and the analytical approach for the firm fixed effect was repeated for the manual time fixed effects model. The model results are shown in appendix C3.2.1. and C3.2.2. shows the result tables for all of the statistical tests.

The statistical test results for time fixed effect are similar to the results of the fixed effect models. The main difference is that the time fixed effect models have a Durbin-Watson score of less than 1. Robust standard errors are therefore used for the time fixed effects model before the Hausman test. Standard errors of the time fixed effects model follow a white noise pattern, just like with firm fixed effects. The Breusch-Pagan test yield only significant results, confirming that robust standard errors are preferred. The endogeneity assumption for fixed effects estimation holds and the VIF-scores are all very low, except for the constants. Just like the firm fixed effects the Shapiro-Wilk test has very significant results, but the Q-Q plots and histograms have a similar shape as firm fixed effects graphs. Overall, the statistical tests show both the firm and time fixed effects models are just as suited to test the hypotheses.

Looking at the results of the manually time fixed effects models (appendix C3.2.1, table 12), the coefficients and standard errors for the included variables are identical to the automatic time fixed effects model in table 11 (Appendix C2). The difference is that the R-squared values are considerably higher due to the inclusion of the yearly dummies. In model 1 with just the control variables 47,6% of the variance between and 6,8% of the variance within firms is explained, resulting in 20,35% of the total variance explained. With additional variables included in each subsequent model, the explained variance within increases and the variance between firms decreases. Apart from the year dummies, the level of EO and EBITDA are significant. These significant coefficients are in line with the expectations following the correlation matrix (table 3). Both the level of EO and EBITDA are very significant (p-value<0,01) in every model they are included. The coefficient for the level of EO in model 7 (3,647) means that for the mean value, employee happiness increases by 0,06 and by 0,18 for the 95th percentile value. The mean value of EBIDTA increases employee happiness by 0,04 at mean level and by 0,14 at the 95th percentile. Because 2016 serves as the reference year, the linear decrease in employee happiness throughout time is clearly reflected by the coefficients of the time dummies. Every year the coefficient has a higher negative value relative to the previous year and every dummy is very significant (p-value<0,01).

4.4 Hypothesis tests

The robustness tests showed that the time fixed effects models (appendix C3.2.1, table 12) are statistically as suitable to test the hypotheses as the firm fixed effects models (table 9). Therefore, both models will be used to test the hypotheses. The reason for the different results will be explained and incorporated in the final approval or rejection of the hypotheses.

Hypothesis 1:
"Entrepreneurial Orientation has a positive effect on Employee Happiness"

To test this hypothesis, the coefficients and significance levels of the level of EO variable need to be interpreted. The firm fixed effects models and time fixed effects models have opposite results for this variable. In the firm fixed effect models the level of EO has a negative insignificant coefficient, while in the time fixed effects models the variable has a positive significant coefficient. In the model without the COVID-19 dummy from the robustness tests, the level of EO is positive yet insignificant. The negative coefficient in the firm fixed effects models therefore seems to be caused by the higher intercept value due to the significant negative coefficient of the COVID-19 dummy. With the inclusion of the level in EO in the time fixed effects model, the within variance increases. This indicates that if a firm increases its level of EO, their employee happiness increases that year too. Based on the level of EO coefficient in the firm fixed effects model, hypothesis 1 would be rejected. Based on the coefficient of the time fixed effects models, hypothesis 1 would be accepted. The time fixed effects coefficient appears to be more accurate, due to the bias included in the EO level variable in the firm fixed effects model with COVID-19 and the increase in explained within variance due to the inclusion of the EO level in the time fixed effects model. Therefore, hypothesis 1 is accepted.

Hypothesis 2:
"An abrupt change in the level Entrepreneurial Orientation has a negative effect on Employee Happiness"

For the abruptness of change in EO variable, the firm fixed effects and time fixed effects model yield contradicting results too. In the firm fixed effects models, the abruptness of change in EO has a significant negative coefficient while the time fixed effects models result in a positive insignificant coefficient. Because the abruptness of change in EO was constructed with a linear regression that included a lag variable, all 2016 entries have a zero value. Furthermore, because the abruptness of change in EO includes both abrupt increases and decreases, the absolute values were used. With employee happiness yearly declining, it correlates negatively significant with the abruptness of change in EO due to the way it was operationalized. That is why the significant negative coefficient in the firm fixed effects models is suspected to explain a lot of the variance from the general time trend in employee happiness. This is confirmed by the robustness test model without all 2016 entries and the time fixed effects models. The abruptness of change in EO turns positive and becomes insignificant in each of these models, proving that the abruptness of change in EO in the firm fixed effects models is biased. In the time fixed effects models, the abruptness of change in EO is totally insignificant in every model, with the effect on the explained variance neglectable. The time fixed effects models seems therefore more accurate and less biased. Hypothesis 2 is therefore rejected.

Hypothesis 3:
"The number of employees mitigates the positive effect of Entrepreneurial Orientation on Employee Happiness"

Hypothesis 4:
"The number of Employees amplifies the negative effect of an abrupt change in the level of Entrepreneurial Orientation on Employee Happiness"

Hypotheses 3 and 4 are tested by looking at the coefficients of the moderator variables. The hypotheses predicted the coefficients to have negative significant values. In none of the estimated models this is the case. In the time fixed effect models, both moderators are insignificant and have a positive value. In the firm fixed effects model, moderator 1 (level of EO * number of employees) is significant but positive and moderator 2 (abruptness of change in EO * number of employees) is negative but insignificant. The explanation for the unexpected significant coefficient for moderator 1 in the firm fixed effects model seems to be caused by the inclusion of the COVID-19 dummy too. In the robustness tests models without the COVID-19 dummy, moderator 1 turned insignificant. Because none of the results align with the hypotheses, both hypothesis 3 and 4 are rejected.

Despite both hypothesis 3 and 4 being rejected, their effects on the dependent variables will be visualized with margin plots. The visual representation might create a better understanding of the effect of the moderators than the coefficients alone. Appendix C3.3 shows the margin plots for moderator 1 and 2 in model 7 for both the firm and time fixed effects. The figures show a linear line for the marginal effect of the moderators. The slope of the linear lines is the same as the coefficient value in regression results tables. The confidence intervals have a cone shape around the marginal line, with narrower intervals around the mean value of the moderators. Of the four margin plots, the one for moderator 1 in the firm fixed effects model has the smallest intervals. This is expected as moderator 1 has a significant coefficient in the firm fixed effects model. Overall, the margin plots follow the regression results, providing no additional insights.

5. Discussion

This study has generated valuable insights that contribute to the scarce existing literature about the relationship between Entrepreneurial Orientation (EO) and Employee Happiness (EH). In this chapter, the theoretical and practical implications of the findings will be discussed. This will be followed by the limitations of the study and recommendations for future research on the EO-EH relationship.

Theoretical implications

The goal of this study was to find the answer to the main research question, being: *"What is the effect of the level of Entrepreneurial Orientation, and the abruptness of change in the level of Entrepreneurial Orientation, on Employee Happiness, and how does firm size affect these effects?".* The answer to the question has theoretical relevance as the relationship between EO and EH is severely underexplored, while both EO and EH are major topics in academic literature. Existing literature about the EO-EH relationship yields conflicting results and over-relies on the cross-sectional data, while both EO and EH are not constant throughout time (Bakker & Demerouti, 2014; Rauch et al., 2009). This study differentiates by using a longitudinal database for the companies included in the S&P500 from 2016 to 2020 (S&P Global, 2024).

The most important finding in this study is the positive relationship between EO and EH when time trends are taken into account. This strengthens the claim that EO can enhance EH through employee satisfaction and organizational commitment (De Clercq & Rius, 2007; Soomro & Shah, 2019), which were based on cross-sectional findings for small and medium enterprises. The overlapping importance of employee autonomy (Deci & Ryan, 1985; Lumpkin et al., 2009) and the increase in individual development opportunities due to the proactive and risk-taking dimensions of EO are examples of the positive relationship between EO and EH.

The second significant result in this study is the negative relationship between the abruptness of change in EO and EH while firm specific characteristics are taken into consideration. The resource exhaustion theory (Gali et al., 2023) explains that abrupt changes in the level of EO increases the chance of resource depletion. Current business processes need to change in order to align with the new firm level strategy. This adaptation process requires significant investments from the firm and demands flexibility from the employees to change their work behaviour. An abrupt change in EO could disrupt the balance between job demands and resources (Bakker & Demerouti, 2014), risking the exhaustion of their human resources (Schaufeli & Bakker, 2004). The negative relationship between the abruptness of EO and EH aligns with this line of argumentation. However, this result seemed to be biased due to the way it was constructed. In the model where the time trend was taken into account, the abruptness of change in EO lost its significant effect on the dependent variable. As the abruptness of change in EO was constructed with a linear regression that included a lag variable, all 2016 entries have a zero value. Between 2016 and 2020, EH decreased every year. The abruptness of change in EO yielded significant results, as it explained the yearly decrease in EH when the time trend was not taken into consideration. The negative relationship between the abruptness of change in EO and EH could therefore not be confirmed.

The third objective of this study was to identify the role of firm size in the relationship of the level of EO and the abruptness of change in EO with EH. EO needs to pervade throughout an entire organization to be successful (Hornsby et al., 2013; W. Wales et al., 2011) and large firms with a lot of employees and hierarchy levels often struggle for alignment throughout the organization (Harvard Business School, 2018). The positive relationship between EO and EH was therefore expected to be weaker in bigger organizations compared to smaller firms. As an abrupt change in the level EO required a swift adaptation from the employees, uncertainty about the new job demands due to poor communication could lead to role ambiguity (Andersén, 2017; Monsen & Wayne Boss, 2009). That is why the negative effect of the abruptness of change in EO on EH was expected to be stronger in bigger organizations. However, none of the results provided evidence that firm size played a role in the relationship of the level of EO or the abruptness of change in EO with EH.

The significant results for included control variables provide context and additional insights. Free cash flow, represented by the firm's EBITDA, had a positive effect on EH in the models including the time trend. This aligns with existing literature that suggests firms with better financial performance have more resources available to invest in their employees, increasing the EH (Mahssouni et al., 2022). The negative relationship between the industry adjusted Tobin's Q and EH suggests that the increased risk of firm failure decreases the EH (Opler & Titman, 1994). Lastly, the negative relationship between the COVID-19 dummy and EH shows that the consequences of the pandemic indeed affected the EH due to a significant decrease in social interactions and disruption of the work environment (Mehta, 2021).

Practical implications

The results of this study show that top-management should be aware that an entrepreneurial strategy can enhance the happiness of their employees. Encouraging innovation, risk-taking and autonomy can create an engaging and inspiring work environment, leading to happier and more productive employees (Harrison et al., 2006; Oswald et al., 2015). Top-management should regard the happiness of their employees not just as an ethical obligation, but as a strategic asset that can be improved with an entrepreneurial orientated strategy. However, abrupt changes in the level of EO should be avoided. The costly adaptation process requires employees to suddenly change their work behaviour. It is key for managers to change the level of EO slowly throughout time and provide support to employees who struggle to adapt to the changing requirements. Support such as clear communication or training sessions keeps the balance between job demands and resources, helping employees to mitigate stress and maintain job satisfaction while adapting to the new demands (Bakker & Demerouti, 2014). If EH is included as one of the KPIs during an EO strategy, a positive effect on business performance is expected (Thompson & Bruk-Lee, 2021). The insignificant results for firm size suggest that strategies to enhance EH through EO can be universally applied across firms of different sizes. Managers should focus on creating a supportive and engaging work environment during an EO strategy, regardless of the number of employees. This includes clear communication, providing growth and development opportunities and rewarding significant accomplishments of employees. The positive relationship between EBITDA and EH underlines that employees are happier in firms that generate more cash that can be reinvested in better work conditions, additional benefits or development opportunities.

Limitations and future research

Although this study provides valuable insights, its limitations should be acknowledged. The decision to use companies in the S&P500 means that the database only includes large public companies. The effects and relationships might differ for startups and small and medium enterprises. Additionally, just using the number of employees as a measure for the firm size might not reflect the full complexity of the organizational structure and its impact on the EO-EH relationship. Future research should consider the inclusion of other firm size dimensions, like salary expenses, hierarchical levels or the number of departments (Dang et al., 2018).

Although every employee is allowed to leave a review on Indeed, using these review ratings as the overall score for employee happiness might include some bias. As exceptional experiences gives people more motivation to leave a review than average experiences, the reviews might be mostly constructed based on outliers. Furthermore, the Indeed reviews are sufficiently reflective for employee happiness as a firm level characteristic, but might not capture the full multidimensional nature of employee happiness. Future research should try to include these multidimensional aspects by constructing the employee happiness based on job satisfaction, organization commitment and well-being components (Fisher, 2010).

One of the biggest limitations in this study relates to the construction of the abruptness of change in EO. The use of a lag variable in the linear regression estimation meant that all 2016 entries had a zero value. As the database includes just 5 entry years, 20% of the entries missed an accurate estimation for the abruptness of change in EO. For all non-zero values, the absolute value was used to include both abrupt increases and decreases. Yet, with the EH yearly decreasing the abruptness of the change in EO incidentally had a significant effect due to the way it was constructed. For the effect of the abruptness of change in EO to be accurately estimated, future research should try to include more entry years or construction without a zero value for all first year entries.

The EBITDA from a bank's financial services is not publicly available knowledge. In future research that wants to account for financial performance, another metric, like profit & loss-ratio, should be chosen or the inclusion of banks in the database should be avoided.

A final limitation that should be mentioned regards the included variables and estimation method. The significant results for the Shapiro-Wilk tests means that normality assumption for the residuals not holds. With less than 10 entries per firm, this is not ideal (Schmidt & Finan, 2018). Furthermore, this study did not consider potential non-linear relationships or the inclusion of a lag variable for the dependent variable in the regression formula. It seems plausible that employee happiness is affected by the employee happiness of last year, as it mostly includes the same people.

The final recommendation for future research is to take the cyclical nature of EO into consideration. Gali et al. (2023) expressed that for an optimal EO strategy a period with a high level of EO is followed by a period with a lower EO level. During high levels of EO exploration of new business opportunities are prioritized, while the exploitation of these opportunities happens with a lower level of EO. Future research should therefore include both the level of EO and if a firm prioritizes exploration or exploitation. This might explain if the priorities and strategy of the firm align, and might show different relationships in different circumstances.

Conclusion

This study uses a longitudinal dataset for firms included in the S&P500 between 2016 and 2020 to answer the following research question: *"What is the effect of the level of Entrepreneurial Orientation, and the abruptness of change in the level of Entrepreneurial Orientation, on Employee Happiness, and how does firm size affect these effects?"*. To answer this question, four hypotheses were constructed and tested with linear regression models. The first hypothesis was accepted because the results showed a significant positive relationship between the level of Entrepreneurial Orientation (EO) and Employee Happiness (EH). This means that high levels of EO, characterized by innovation, risk-taking and employee autonomy enhance EH via employee satisfaction and organizational commitment. This aligns with existing theories such as the Job Demands-Resource theory, and provides evidence for the idea that an entrepreneurial culture can create an engaging work environment. The use of a longitudinal dataset adds to previous claims about a positive EO-EH relationship, which were based on cross-sectional data.

The relationship between the abruptness of change in EO and EH was more complex, with the second hypothesis ultimately rejected. Initially a significant negative relationship was found, but further analysis indicated that the result might be biased due to the construction of the abruptness of change in EO variable, and the time trend in EH. The negative impact could therefore not be confirmed. Firm size was found to have no significant effect on each of the two relationships above, meaning that both hypotheses 3 and 4 were rejected. This suggests that the positive relationship between the level of EO and EH is applicable to any public company regardless of the number of employees.

Answering the main research question, entrepreneurial orientation has a positive effect on employee happiness. The abruptness of change in entrepreneurial orientation is suspected to have a negative impact on employee happiness, but due to a lack of robust proof, this could not be confirmed. The size of the firm, measured by the number of employees, does not impact the EO-EH relationship, nor the effects of the abruptness of change in entrepreneurial orientation on employee happiness. As the data only consist of publicly listed companies, generalizing these results to startups or small and medium-size enterprises requires caution.

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7. Appendices

Appendix A – Theoretical Background

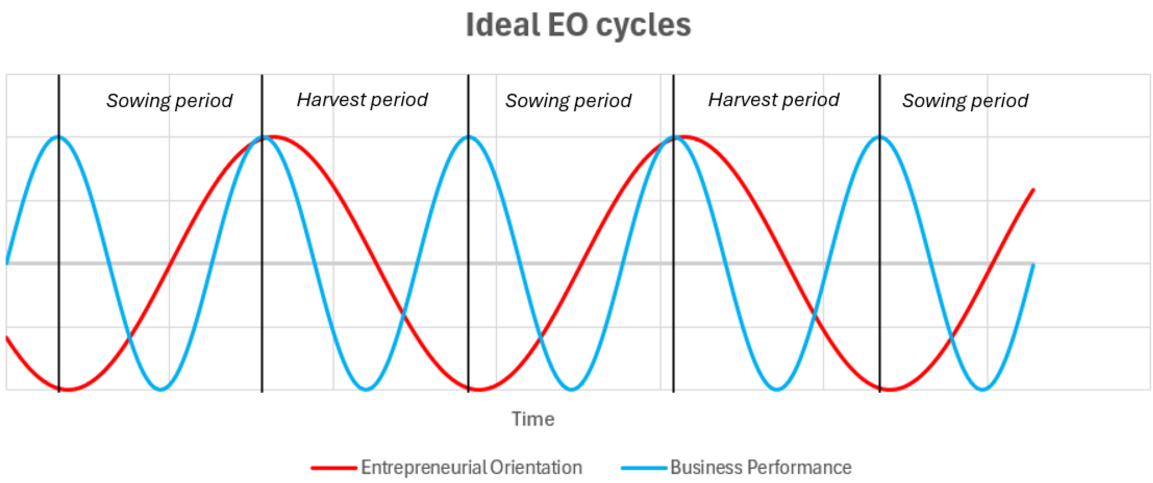


Figure 1: Authors interpretation of ideal EO cycles

Figure 1 shows the visual sketch of the authors interpretation of ideal EO-cycle following the explanation of Gali et al. (2023). The figure shows that both a firms business performance and EO level fluctuate over time. For each two cycles in business performance, the firm has one cycle in the level of EO. Once a firms notices that their business performance is dropping, they need to adapt their level of EO. They need to do this slowly because an abrupt change would amplify the decrease in firm performance. Each cycle in business performance has a clear objective. When the firm has a low level of EO and the business performance starts to decrease, the firm starts to increase their EO level. The objective of increasing the level of EO is to find new business opportunities. This is labelled as the sowing period. With new business opportunities the firm performance starts to increase again, until exploitation is neglected to much in favour of exploration. When the firm becomes aware of this decrease in business performance, they start to decrease their EO level again. This is the start of the harvest period, where exploitation of the identified business opportunities from the sowing period is prioritized. This will increase the business performance again because the projects will be executed and deliver the required returns, until the business needs new business opportunities again. This will start the next EO cycle, starting with a sowing period. By splitting the EO cycle in a sowing and harvest period the firm contains the EE at manageable levels, reducing the risk on resource exhaustion.

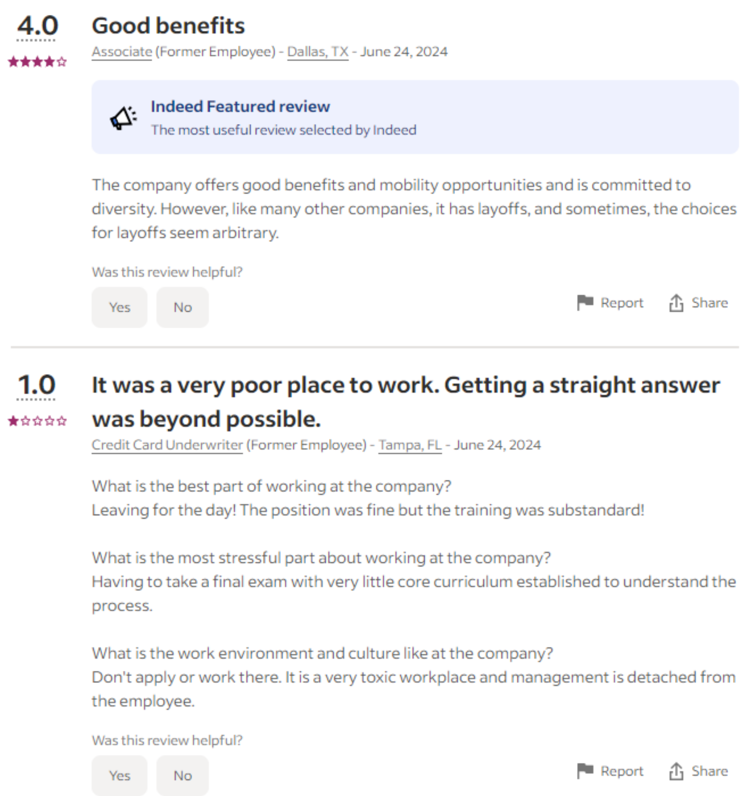
Appendix B – Methodology

Appendix B1: Indeed.com

Indeed (Indeed.com, 2023) is an employment website from the United States with job listings all over the world. Indeed is currently active in 60 countries and available in 28 languages. More than 3,5 million employers use Indeed to hire new staff and they have over 350 million unique monthly visitors. Indeed's main focus is on the experience of the job seeker. Important features are the ability to filter on education, salary, spoken language, kind of contract or kind of job makes it easier to navigate through all the options. Furthermore, they have the option to compare different jobs and give suggestions of similar job options. A key part of the value Indeed offers, is the huge amount of reviews employees have given their employers. Job seekers can read all about other people experiences, similar to Airbnb (Airbnb, 2024) or UBER (UBER, 2024). Because these reviews are so valuable to Indeed, they decided that everyone who worked at the company could leave their review. Indeed takes the responsibility to check if the person who gave the review has been or is working at the company before showing it online.

Figure 2 shows a screenshot of two reviews for JPMorgan Chase & Co. Each review consists of a 1-5 rating, the date the review was given, the position of the employee, if they are still working there, the work location and a text that explains the review score. By reading past experiences, job seekers can decide if this company is something they are interested in or not. Apart from the individual reviews, Indeed shows photos, Q&A's and a lot more information for each employer.

For employers Indeed is important as it their rating is a big influence of the public opinion about the company. If the average review rating is around 2, this will not just repel job seekers but investors or possible clients too. It is a public accessible platform and therefore acts a soft check for companies to take care of their employees' health, well-being and happiness.


4.0
Good benefits
Associate (Former Employee) - Dallas, TX - June 24, 2024
Indeed Featured review
The most useful review selected by Indeed
The company offers good benefits and mobility opportunities and is committed to diversity. However, like many other companies, it has layoffs, and sometimes, the choices for layoffs seem arbitrary.
Was this review helpful?
Yes No Report Share

1.0
It was a very poor place to work. Getting a straight answer was beyond possible.
Credit Card Underwriter (Former Employee) - Tampa, FL - June 24, 2024
What is the best part of working at the company?
Leaving for the day! The position was fine but the training was substandard!
What is the most stressful part about working at the company?
Having to take a final exam with very little core curriculum established to understand the process.
What is the work environment and culture like at the company?
Don't apply or work there. It is a very toxic workplace and management is detached from the employee.
Was this review helpful?
Yes No Report Share

Figure 2: Review Ratings Indeed.com (JPMorgan Chase & Co)

Appendix B2: Industry adjusted Tobin's Q

The industry adjusted Tobin's Q is a measure that shows if a company is overvalued or undervalued relative to its competitors in their industry group. The industry adjusted Tobin's Q was calculated in three steps. First the total debt of all companies needed to calculated. This was done with the following formula:

$$Total\ Debt = Net\ Current\ Debt + Net\ Long\ Term\ Debt + Cash\ on\ Hand$$

The total debt is needed in order to calculate the value of the firm. By dividing the value of the firm over the total value of its assets you get the Tobin's Q. If a company has a high Tobin's Q, it means that the company is surrounded by a lot of hype. The valuation of the firm was done by multiplying the number of shares outstanding times the closing share price at the end of December. This results in the following formula:

$$Tobin's\ Q = \frac{(\#Shares\ outstanding * Closing\ price\ december) + Total\ Debt}{Total\ Assets}$$

To adjusted the Tobin's Q to the industry group average, the average Tobin's Q for each industry group needed to be calculated. The industry group averages were calculated for each of the groups of the Global Industry Classification Standard (GICS, 2024). Subtracting these averages from the calculated Tobin's Q of the entry results in the industry adjusted Tobin's Q.

$$Industry\ adjusted\ Tobin's\ Q = Tobin's\ Q - Industry\ group\ average(Tobin's\ Q)$$

The calculation of the industry adjusted Tobin's Q was the first modification made to the data. The values are therefore adjusted by the all the 2505 entries that were originally in the database. This was done because this is a metric relative to the population, not to the sample used in the analysis.

Appendix B3: Variables per model

Table 10: Variables per model

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Control variables	X	X	X	X	X	X	X
Level of EO	-	X	X	X	X	X	X
Abruptness change EO	-	-	X	X	X	X	X
Number of Employees	-	-	-	X	X	X	X
EO*EMP	-	-	-	-	X	-	X
acEO*EMP	-	-	-	-	-	X	X

EO = Entrepreneurial Orientation; acEO = Abruptness change EO

Table 10 shows which variables are included in each of the 7 models estimated for this study. Each model contains the control variables. In every subsequent model one additional variable is added to single out the effect this model has on the dependent variable and the effects of the other variables. To see how each of the moderators act independent of each other, model 5 and 6 contain just one of the two.

Appendix C – Results

Appendix C1: Python codes

C1.1: First difference with Breusch-Godfrey test

```python
import pandas as pd
import numpy as np
from linearmodels.panel import FirstDifferenceOLS
import statsmodels.api as sm
from statsmodels.stats.diagnostic import acorr_breusch_godfrey

# Load your data into a pandas DataFrame from an Excel file
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Function to manually difference the data
def difference_data(df, entity, time, variables):
    df_diff = df.copy()
    df_diff[variables] = df_diff.groupby(entity)[variables].diff()
    df_diff = df_diff.dropna()
    return df_diff

# Define the formulas for the regression
formulas = [
    'AvgReviewRating ~ Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
]

# Differencing the data
variables = ['AvgReviewRating', 'Adjusted_TQ', 'Resource_Slack', 'Debt_Equity_Ratio', 'EBITDA', 'DUM5', 'AvgEO', 'DDEO_ABS', 'Numb_EMP1000', 'DDEO_EMP1', 'EO_EMP1']
df_diff = difference_data(df, 'Ticker', 'Year', variables)

# Fit the models using first-differences estimator and run diagnostics
for i, formula in enumerate(formulas, start=1):
    # Fit the model using first-differences estimator with clustered standard errors
    model = FirstDifferenceOLS.from_formula(formula, data=df)
    result = model.fit()
    print(f"Summary for First-Differences Model M{i}:\n", result.summary)

    # Fit the model using statsmodels OLS for the Breusch-Godfrey test
    ols_model = sm.OLS.from_formula(formula, data=df_diff).fit(cov_kwds={'maxlags': 1})

    # Breusch-Godfrey test
    bg_test = acorr_breusch_godfrey(ols_model, nlags=1)
    print(f"Breusch-Godfrey Test for First-Differences Model M{i}:\n", bg_test)
    print("\n")

```

C1.2: First difference (standard error = kernel)

```python
import pandas as pd
import numpy as np
from linearmodels.panel import FirstDifferenceOLS
import statsmodels.api as sm
from statsmodels.stats.diagnostic import acorr_breusch_godfrey

# Load your data into a pandas DataFrame from an Excel file
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Function to manually difference the data
def difference_data(df, entity, time, variables):
    df_diff = df.copy()
    df_diff[variables] = df_diff.groupby(entity)[variables].diff()
    df_diff = df_diff.dropna()
    return df_diff

# Define the formulas for the regression
formulas = [
    'AvgReviewRating ~ Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'AvgReviewRating ~ AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5'
]

# Differencing the data
variables = ['AvgReviewRating', 'Adjusted_TQ', 'Resource_Slack', 'Debt_Equity_Ratio', 'EBITDA', 'DUM5', 'AvgEO', 'DDEO_ABS', 'Numb_EMP1000', 'DDEO_EMP1', 'EO_EMP1']
df_diff = difference_data(df, 'Ticker', 'Year', variables)

# Fit the models using first-differences estimator and run diagnostics
for i, formula in enumerate(formulas, start=1):
    # Fit the model using first-differences estimator with clustered standard errors
    model = FirstDifferenceOLS.from_formula(formula, data=df)
    result = model.fit(cov_type='kernel')
    print(f"Summary for First-Differences Model M{i}:\n", result.summary)
```

C1.3: Fixed effects and random effects with Durbin-Watson test

```
# Load your data into a pandas DataFrame from an Excel file
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Define the formula for the regression
formula_M1 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5'
formula_M2 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO'
formula_M3 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS'
formula_M4 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000'
formula_M5 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1'
formula_M6 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1'
formula_M7 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit()
    return result

# Function to fit the random effects model and return results
def fit_random_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    model = RandomEffects(y, X)
    result = model.fit()
    return result

# Fit the fixed effects models
fixed_effects_result_M1 = fit_fixed_effects_model(formula_M1)
fixed_effects_result_M2 = fit_fixed_effects_model(formula_M2)
fixed_effects_result_M3 = fit_fixed_effects_model(formula_M3)
fixed_effects_result_M4 = fit_fixed_effects_model(formula_M4)
fixed_effects_result_M5 = fit_fixed_effects_model(formula_M5)
fixed_effects_result_M6 = fit_fixed_effects_model(formula_M6)
fixed_effects_result_M7 = fit_fixed_effects_model(formula_M7)

# Fit the random effects models
random_effects_result_M1 = fit_random_effects_model(formula_M1)
random_effects_result_M2 = fit_random_effects_model(formula_M2)
random_effects_result_M3 = fit_random_effects_model(formula_M3)
random_effects_result_M4 = fit_random_effects_model(formula_M4)
random_effects_result_M5 = fit_random_effects_model(formula_M5)
random_effects_result_M6 = fit_random_effects_model(formula_M6)
random_effects_result_M7 = fit_random_effects_model(formula_M7)
```

```
print(fixed_effects_result_M1.summary)
print("\n")
print(random_effects_result_M1.summary)
print("\n")
print(fixed_effects_result_M2.summary)
print("\n")
print(random_effects_result_M2.summary)
print("\n")
print(fixed_effects_result_M3.summary)
print("\n")
print(random_effects_result_M3.summary)
print("\n")
print(fixed_effects_result_M4.summary)
print("\n")
print(random_effects_result_M4.summary)
print("\n")
print(fixed_effects_result_M5.summary)
print("\n")
print(random_effects_result_M5.summary)
print("\n")
print(fixed_effects_result_M6.summary)
print("\n")
print(random_effects_result_M6.summary)
print("\n")
print(fixed_effects_result_M7.summary)
print("\n")
print(random_effects_result_M7.summary)
print("\n")

# Check for autocorrelation using Durbin-Watson test
def durbin_watson_test(result):
    dw_stat = durbin_watson(result.resids)
    return dw_stat

dw_stat_M1 = durbin_watson_test(fixed_effects_result_M1)
dw_stat_M2 = durbin_watson_test(fixed_effects_result_M2)
dw_stat_M3 = durbin_watson_test(fixed_effects_result_M3)
dw_stat_M4 = durbin_watson_test(fixed_effects_result_M4)
dw_stat_M5 = durbin_watson_test(fixed_effects_result_M5)
dw_stat_M6 = durbin_watson_test(fixed_effects_result_M6)
dw_stat_M7 = durbin_watson_test(fixed_effects_result_M7)

print("\nDurbin-Watson Test for Fixed Effects Model 1 (M1):", dw_stat_M1)
print("\nDurbin-Watson Test for Fixed Effects Model 2 (M2):", dw_stat_M2)
print("\nDurbin-Watson Test for Fixed Effects Model 3 (M3):", dw_stat_M3)
print("\nDurbin-Watson Test for Fixed Effects Model 4 (M4):", dw_stat_M4)
print("\nDurbin-Watson Test for Fixed Effects Model 5 (M5):", dw_stat_M5)
print("\nDurbin-Watson Test for Fixed Effects Model 6 (M6):", dw_stat_M6)
print("\nDurbin-Watson Test for Fixed Effects Model 7 (M7):", dw_stat_M7)
```

```
dw_stat_M1 = durbin_watson_test(random_effects_result_M1)
dw_stat_M2 = durbin_watson_test(random_effects_result_M2)
dw_stat_M3 = durbin_watson_test(random_effects_result_M3)
dw_stat_M4 = durbin_watson_test(random_effects_result_M4)
dw_stat_M5 = durbin_watson_test(random_effects_result_M5)
dw_stat_M6 = durbin_watson_test(random_effects_result_M6)
dw_stat_M7 = durbin_watson_test(random_effects_result_M7)

print("\nDurbin-Watson Test for Random Effects Model 1 (M1):", dw_stat_M1)
print("\nDurbin-Watson Test for Random Effects Model 2 (M2):", dw_stat_M2)
print("\nDurbin-Watson Test for Random Effects Model 3 (M3):", dw_stat_M3)
print("\nDurbin-Watson Test for Random Effects Model 4 (M4):", dw_stat_M4)
print("\nDurbin-Watson Test for Random Effects Model 5 (M5):", dw_stat_M5)
print("\nDurbin-Watson Test for Random Effects Model 6 (M6):", dw_stat_M6)
print("\nDurbin-Watson Test for Random Effects Model 7 (M7):", dw_stat_M7)
```

C1.4: Fixed effects vs. First differences – Pattern of residuals

```python

# Load your data into a pandas DataFrame from an Excel file
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Define the formula for the regression
formulas = {
    'M1': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'M2': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO',
    'M3': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS',
    'M4': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000',
    'M5': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1',
    'M6': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1',
    'M7': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'
}

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    y = y.iloc[:, 0]  # Convert y to a Series
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit()
    return result

# Fit the fixed effects models
results = {name: fit_fixed_effects_model(formula) for name, formula in formulas.items()}

# Print summaries
for name, result in results.items():
    print(f"Summary for {name}:\n")
    print(result.summary)
    print("\n")

# Function to plot residuals and perform Durbin-Watson test
def analyze_residuals(result, model_name):
    residuals = result.resids
    plt.figure(figsize=(10, 6))
    plt.plot(residuals.values)  # Ensure residuals are in a numeric array format
    plt.title(f'Residuals of {model_name}')
    plt.xlabel('Observations')
    plt.ylabel('Residuals')
    plt.show()

    # Durbin-Watson test
    dw_stat = durbin_watson(residuals.values)  # Ensure residuals are in a numeric array format
    print(f'Durbin-Watson statistic for {model_name}: {dw_stat}')

# Analyze residuals for each model
for name, result in results.items():
    analyze_residuals(result, name)
```

C1.5: Hausman test

```python
# Perform Hausman test to compare fixed effects and random effects models
def hausman_test(fe_result, re_result):
    b = fe_result.params
    B = re_result.params
    v_b = fe_result.cov
    v_B = re_result.cov
    df = b.shape[0]

    diff = b - B
    diff_cov = v_b - v_B
    stat = diff.T @ np.linalg.inv(diff_cov) @ diff

    pval = stats.chi2.sf(stat, df)
    return stat, pval

hausman_test_M1 = hausman_test(fixed_effects_result_M1, random_effects_result_M1)
hausman_test_M2 = hausman_test(fixed_effects_result_M2, random_effects_result_M2)
hausman_test_M3 = hausman_test(fixed_effects_result_M3, random_effects_result_M3)
hausman_test_M4 = hausman_test(fixed_effects_result_M4, random_effects_result_M4)
hausman_test_M5 = hausman_test(fixed_effects_result_M5, random_effects_result_M5)
hausman_test_M6 = hausman_test(fixed_effects_result_M6, random_effects_result_M6)
hausman_test_M7 = hausman_test(fixed_effects_result_M7, random_effects_result_M7)

print("\nHausman Test for Model 1 (M1):", hausman_test_M1)
print("\nHausman Test for Model 2 (M2):", hausman_test_M2)
print("\nHausman Test for Model 3 (M3):", hausman_test_M3)
print("\nHausman Test for Model 4 (M4):", hausman_test_M4)
print("\nHausman Test for Model 5 (M5):", hausman_test_M5)
print("\nHausman Test for Model 6 (M6):", hausman_test_M6)
print("\nHausman Test for Model 7 (M7):", hausman_test_M7)
```

C1.6: Breusch-pagan test for fixed effects

```python
# Check for heteroscedasticity using Breusch-Pagan test
def breusch_pagan_test(result, formula, df):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    bp_test = het_breuschpagan(result.resids, X)
    return bp_test

bp_test_M1 = breusch_pagan_test(fixed_effects_result_M1, formula_M1, df)
bp_test_M2 = breusch_pagan_test(fixed_effects_result_M2, formula_M2, df)
bp_test_M3 = breusch_pagan_test(fixed_effects_result_M3, formula_M3, df)
bp_test_M4 = breusch_pagan_test(fixed_effects_result_M4, formula_M4, df)
bp_test_M5 = breusch_pagan_test(fixed_effects_result_M5, formula_M5, df)
bp_test_M6 = breusch_pagan_test(fixed_effects_result_M6, formula_M6, df)
bp_test_M7 = breusch_pagan_test(fixed_effects_result_M7, formula_M7, df)

print("\nBreusch-Pagan Test for Fixed Effects Model 1 (M1):", bp_test_M1)
print("\nBreusch-Pagan Test for Fixed Effects Model 2 (M2):", bp_test_M2)
print("\nBreusch-Pagan Test for Fixed Effects Model 3 (M3):", bp_test_M3)
print("\nBreusch-Pagan Test for Fixed Effects Model 4 (M4):", bp_test_M4)
print("\nBreusch-Pagan Test for Fixed Effects Model 5 (M5):", bp_test_M5)
print("\nBreusch-Pagan Test for Fixed Effects Model 6 (M6):", bp_test_M6)
print("\nBreusch-Pagan Test for Fixed Effects Model 7 (M7):", bp_test_M7)
```

C1.8: Fixed effects with statistical tests (standard error = robust)

```python
# Load your data into a pandas DataFrame from an Excel file
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Define the formula for the regression
formula_M1 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5'
formula_M2 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO'
formula_M3 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS'
formula_M4 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000'
formula_M5 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1'
formula_M6 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1'
formula_M7 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit(cov_type='robust')
    return result

# Function to fit the random effects model and return results
def fit_random_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    model = RandomEffects(y, X)
    result = model.fit()
    return result

# Fit the fixed effects models
fixed_effects_result_M1 = fit_fixed_effects_model(formula_M1)
fixed_effects_result_M2 = fit_fixed_effects_model(formula_M2)
fixed_effects_result_M3 = fit_fixed_effects_model(formula_M3)
fixed_effects_result_M4 = fit_fixed_effects_model(formula_M4)
fixed_effects_result_M5 = fit_fixed_effects_model(formula_M5)
fixed_effects_result_M6 = fit_fixed_effects_model(formula_M6)
fixed_effects_result_M7 = fit_fixed_effects_model(formula_M7)

print(fixed_effects_result_M1.summary)
print(fixed_effects_result_M2.summary)
print(fixed_effects_result_M3.summary)
print(fixed_effects_result_M4.summary)
print(fixed_effects_result_M5.summary)
print(fixed_effects_result_M6.summary)
print(fixed_effects_result_M7.summary)

# Check for normality of residuals using Shapiro-Wilk test
def shapiro_wilk_test(result):
    shapiro_test = shapiro(result.resids)
    return shapiro_test
```

```python
# Check for normality of residuals using Shapiro-Wilk test
def shapiro_wilk_test(result):
    shapiro_test = shapiro(result.resids)
    return shapiro_test

shapiro_test_M1 = shapiro_wilk_test(fixed_effects_result_M1)
shapiro_test_M2 = shapiro_wilk_test(fixed_effects_result_M2)
shapiro_test_M3 = shapiro_wilk_test(fixed_effects_result_M3)
shapiro_test_M4 = shapiro_wilk_test(fixed_effects_result_M4)
shapiro_test_M5 = shapiro_wilk_test(fixed_effects_result_M5)
shapiro_test_M6 = shapiro_wilk_test(fixed_effects_result_M6)
shapiro_test_M7 = shapiro_wilk_test(fixed_effects_result_M7)

print("\nShapiro-Wilk Test for Fixed Effects Model 1 (M1):", shapiro_test_M1)
print("\nShapiro-Wilk Test for Fixed Effects Model 2 (M2):", shapiro_test_M2)
print("\nShapiro-Wilk Test for Fixed Effects Model 3 (M3):", shapiro_test_M3)
print("\nShapiro-Wilk Test for Fixed Effects Model 4 (M4):", shapiro_test_M4)
print("\nShapiro-Wilk Test for Fixed Effects Model 5 (M5):", shapiro_test_M5)
print("\nShapiro-Wilk Test for Fixed Effects Model 6 (M6):", shapiro_test_M6)
print("\nShapiro-Wilk Test for Fixed Effects Model 7 (M7):", shapiro_test_M7)

# Check for multicollinearity
def check_multicollinearity(df, formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    X = add_constant(X)
    vif_data = pd.DataFrame()
    vif_data["Variable"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(len(X.columns))]
    return vif_data

vif_M1 = check_multicollinearity(df, formula_M1)
vif_M2 = check_multicollinearity(df, formula_M2)
vif_M3 = check_multicollinearity(df, formula_M3)
vif_M4 = check_multicollinearity(df, formula_M4)
vif_M5 = check_multicollinearity(df, formula_M5)
vif_M6 = check_multicollinearity(df, formula_M6)
vif_M7 = check_multicollinearity(df, formula_M7)

print("\nVIF for Fixed Effects Model 1 (M1):")
print(vif_M1)
print("\nVIF for Fixed Effects Model 2 (M2):")
print(vif_M2)
print("\nVIF for Fixed Effects Model 3 (M3):")
print(vif_M3)
print("\nVIF for Fixed Effects Model 4 (M4):")
print(vif_M4)
print("\nVIF for Fixed Effects Model 5 (M5):")
print(vif_M5)
print("\nVIF for Fixed Effects Model 6 (M6):")
print(vif_M6)
print("\nVIF for Fixed Effects Model 7 (M7):")
print(vif_M7)
```

C1.9: Testing for endogeneity – explanatory variables on residuals

```python
# Load your data into a pandas DataFrame from an Excel file
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Define the formula for the regression
formulas = {
    'M1': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'M2': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO',
    'M3': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS',
    'M4': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000',
    'M5': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1',
    'M6': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1',
    'M7': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'
}

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    y = y.iloc[:, 0]  # Convert y to a Series
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit(cov_type='robust')
    return result

# Fit the fixed effects models
fixed_effects_results = {name: fit_fixed_effects_model(formula) for name, formula in formulas.items()}

import statsmodels.api as sm

# Function to regress residuals on explanatory variables and print summary
def regress_residuals_on_explanatory_vars(residuals, explanatory_vars):
    explanatory_vars = sm.add_constant(explanatory_vars)
    model = sm.OLS(residuals, explanatory_vars)
    result = model.fit()
    print(result.summary())

# Get the residuals from the fixed effects and random effects models
residuals_FE = {name: result.resids for name, result in fixed_effects_results.items()}


# Regress residuals on explanatory variables for fixed effects models
for name, residuals in residuals_FE.items():
    print(f"Fixed Effects Model {name} Residuals Regression Summary:")
    explanatory_vars = dmatrices(formulas[name], data=df, return_type='dataframe')[1]
    regress_residuals_on_explanatory_vars(residuals, explanatory_vars)
```

C1.10: Normality plots – Histogram & Q-Q plots

```python

# Define the formula for the regression
formulas = {
    'M1': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5',
    'M2': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO',
    'M3': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS',
    'M4': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000',
    'M5': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1',
    'M6': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + DDEO_EMP1',
    'M7': 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'
}

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    y = y.iloc[:, 0]  # Convert y to a Series
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit(cov_type='robust')
    return result

# Fit the fixed effects models
fixed_effects_results = {name: fit_fixed_effects_model(formula) for name, formula in formulas.items()}

# Check for normality of residuals using Shapiro-Wilk test
def shapiro_wilk_test(result):
    shapiro_test = shapiro(result.resids)
    return shapiro_test

# Plot residuals and check for normality
def plot_residuals(result, title):
    residuals = result.resids.dropna()
    plt.figure(figsize=(12, 6))

    # Residuals distribution
    plt.subplot(1, 2, 1)
    plt.hist(residuals, bins=30, edgecolor='k', alpha=0.7)
    plt.title(f'{title} Residuals Distribution')
    plt.xlabel('Residuals')
    plt.ylabel('Frequency')

    # Q-Q plot
    plt.subplot(1, 2, 2)
    sm.qqplot(residuals, line='s')
    plt.title(f'{title} Q-Q Plot')

    plt.tight_layout()
    plt.show()

# Perform Shapiro-Wilk test and plot residuals for each model
shapiro_tests = {}
for name, result in fixed_effects_results.items():
    shapiro_tests[name] = shapiro_wilk_test(result)
    plot_residuals(result, f'Model {name}')

# Print Shapiro-Wilk test results
for name, test_result in shapiro_tests.items():
    print(f"\nShapiro-Wilk Test for {name}:", test_result)
```

C1.11: Robustness model Logged variables

```python
# Apply log transformation to skewed variables
def log_transform(series):
    return np.log1p(series.clip(lower=0))

df['AvgReviewRating'] = log_transform(df['AvgReviewRating'])
df['AvgEO'] = log_transform(df['AvgEO'])
df['DDEO_ABS'] = log_transform(df['DDEO_ABS'])
df['Numb_EMP1000'] = log_transform(df['Numb_EMP1000'])
df['Adjusted_TQ'] = log_transform(df['Adjusted_TQ'])
df['Resource_Slack'] = log_transform(df['Resource_Slack'])
df['Debt_Equity_Ratio'] = log_transform(df['Debt_Equity_Ratio'])
df['EBITDA'] = log_transform(df['EBITDA'])
df['DDEO_EMP1'] = log_transform(df['DDEO_EMP1'])
df['EO_EMP1'] = log_transform(df['EO_EMP1'])


# Define the formula for the regression using the standardized data
formula_M7 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit()
    return result



# Fit the fixed effects models
fixed_effects_result_M7 = fit_fixed_effects_model(formula_M7)

# Print the regression summary
print(fixed_effects_result_M7.summary)
```

C1.12: Robustness model without outliers

```python
# Define the list of variables in the formula
variables = [
    'AvgReviewRating', 'Adjusted_TQ', 'Resource_Slack', 'Debt_Equity_Ratio',
    'EBITDA', 'Numb_EMP1000', 'DDEO_ABS',
]

# Function to identify outliers
def identify_outliers(data, var):
    Q1 = data[var].quantile(0.10)
    Q3 = data[var].quantile(0.90)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
    outliers = data[(data[var] < lower_bound) | (data[var] > upper_bound)]
    return outliers.index.tolist()

# Identify outliers for each variable
outlier_indices = set()
for var in variables:
    outliers = identify_outliers(df, var)
    outlier_indices.update(outliers)

# Exclude outliers from the dataset
df_clean = df.drop(index=outlier_indices)

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df_clean = df_clean.set_index(['Ticker', 'Year'])

# Define the formula for the regression
formula_M6 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'

# Perform the fixed effects regression with robust standard errors
y, X = dmatrices(formula_M6, data=df_clean, return_type='dataframe')
model = PanelOLS(y, X, entity_effects=True)
result = model.fit(cov_type='robust')

# Print the regression results
print(result.summary)
```

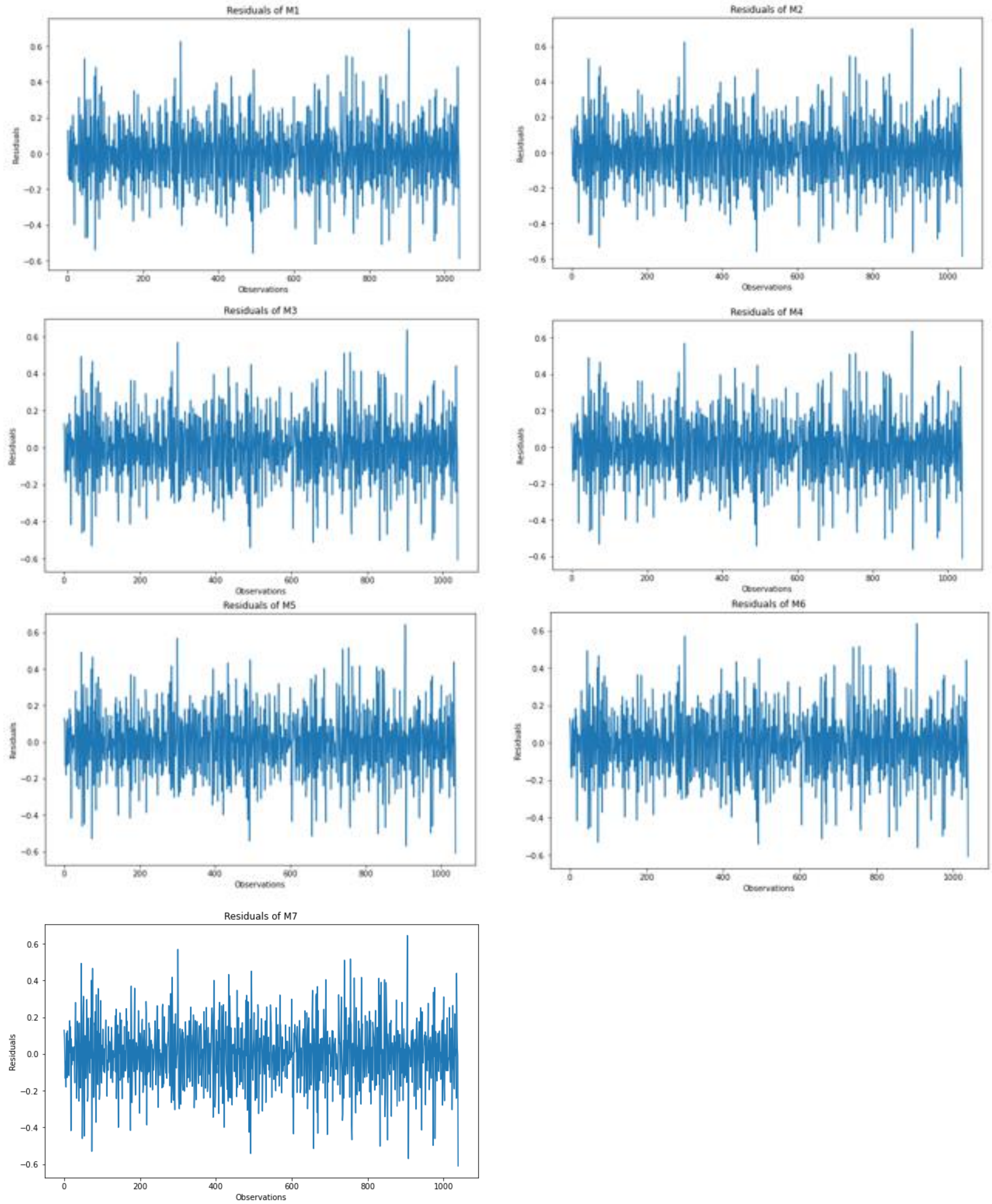
Margin plots

```python
# Load your data into a pandas DataFrame
df = pd.read_excel('Final database5.xlsx')

# Convert the DataFrame to a MultiIndex DataFrame with panel data structure
df = df.set_index(['Ticker', 'Year'])

# Define the formula for the regression
formula_M6 = 'AvgReviewRating ~ 1 + Adjusted_TQ + Resource_Slack + Debt_Equity_Ratio + EBITDA + DUM5 + AvgEO + DDEO_ABS + Numb_EMP1000 + EO_EMP1 + DDEO_EMP1'

# Function to fit the fixed effects model and return results
def fit_fixed_effects_model(formula):
    y, X = dmatrices(formula, data=df, return_type='dataframe')
    model = PanelOLS(y, X, entity_effects=True)
    result = model.fit(cov_type='robust')
    return result, X

# Fit the fixed effects model
fixed_effects_result_M6, X_M6 = fit_fixed_effects_model(formula_M6)

# Define the interaction term
interaction_term = 'DDEO_EMP1'

# Define a range of values for the interaction term
at_values = np.linspace(df[interaction_term].min(), df[interaction_term].max(), 10)

# Function to calculate margins and confidence intervals
def calculate_margins_and_ci(model, X, params, interaction_term, at_values):
    margins = []
    lower_ci = []
    upper_ci = []

    for value in at_values:
        X_adjusted = X.copy()
        X_adjusted[interaction_term] = value

        margin = np.dot(X_adjusted, params).mean()
        margins.append(margin)

        # Calculate standard errors
        se = np.sqrt(np.diag(np.dot(X_adjusted, np.dot(model.cov, X_adjusted.T))))
        ci = 1.96 * se.mean()
        lower_ci.append(margin - ci)
        upper_ci.append(margin + ci)

    return margins, lower_ci, upper_ci

# Calculate margins and confidence intervals
margins, lower_ci, upper_ci = calculate_margins_and_ci(fixed_effects_result_M6, X_M6, fixed_effects_result_M6.params, interaction_term, at_values)

# Plot margins with confidence intervals
def plot_margins_with_ci(at_values, margins, lower_ci, upper_ci, interaction_term):
    plt.figure(figsize=(10, 6))
    plt.plot(at_values, margins, marker='o', linestyle='-')
    plt.fill_between(at_values, lower_ci, upper_ci, color='b', alpha=0.2)
    plt.xlabel('Moderator 2 (acEO*EMP)', fontsize=14)  # Increased by 20%
    plt.ylabel('Predicted Employee Happiness', fontsize=14)  # Increased by 20%
    plt.title(f'Marginal Effects of Moderator 2 on Employee Happiness (Firm fixed effects)', fontsize=16, pad=10)  # Increased by 30% and added pad
    plt.grid(axis='y')  # Include only horizontal grid lines
    plt.show()

plot_margins_with_ci(at_values, margins, lower_ci, upper_ci, interaction_term)
```

Appendix C2: Plots and graphs statistical tests

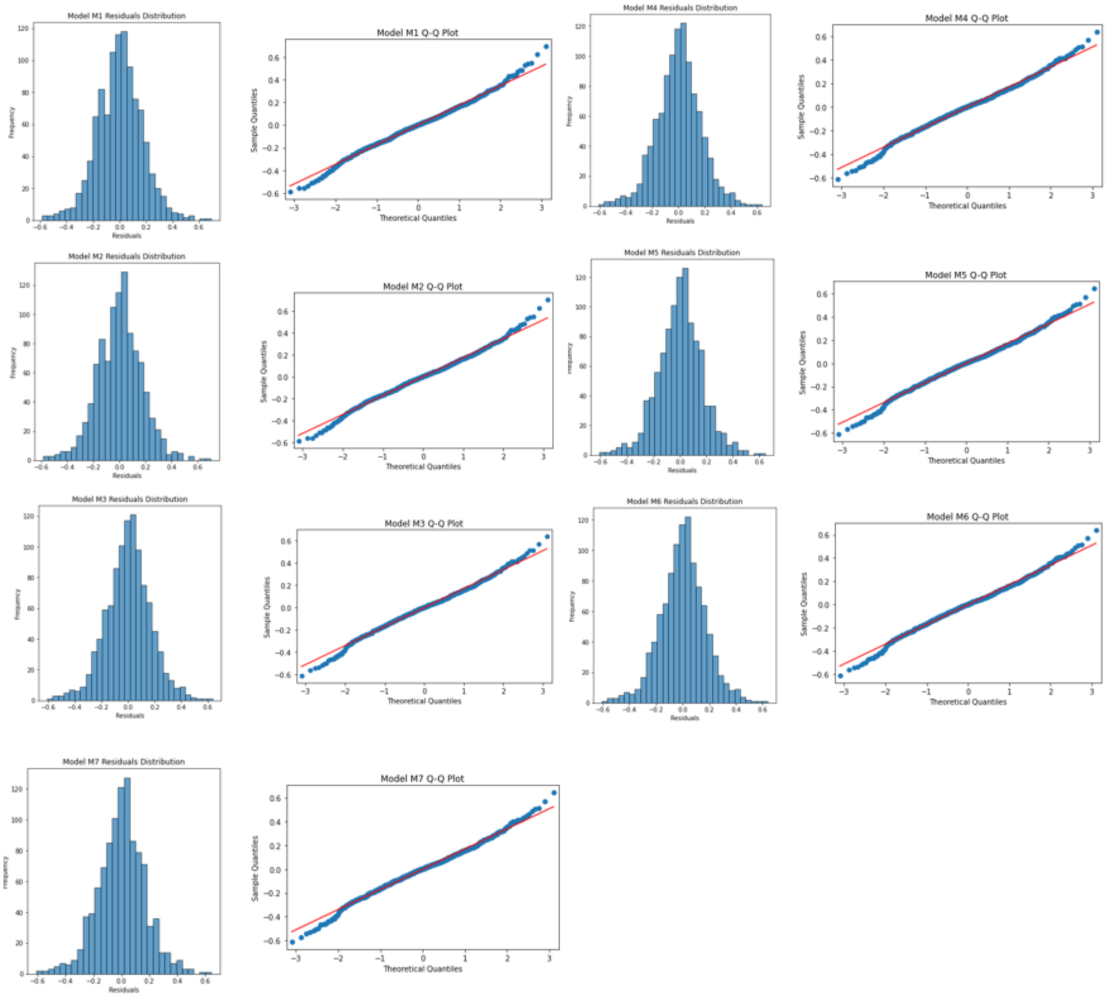
C2.1: Residuals firm fixed effects models

Figure 3-9: Pattern of residuals firm fixed effects



C2.2: Histograms and Q-Q plots

Figure 10-23: Histogram and Q-Q plots of Residuals firm fixed effects



Appendix C3: Alternative results

C3.1.1: Results Robustness

Table 11: Results robustness checks

	Without COVID-19 dummy		*Time fixed effects*		*Without 2016 (a)*		*No control variables*		*Variables log transformed*		*Excluding outliers (b)*	
	Coefficient	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**
Intercept	3,7069**	0,0462	3,5142**	0,0388	3,6602**	0,0471	3,7223**	0,0366	1,713**	0,0476	3,697**	0,0867
Adjusted Tobin's Q	-0,0321**	0,0104	-0,0023	0,0093	-0,0152	0,0119	X	X	-0,0162*	0,0066	-0,0357	0,0215
Resource Slack	0,0217	0,0177	-0,0063	0,0103	0,0276	0,0190	X	X	0,0189	0,0122	0,0609	0,0343
Debt-to-Equity Ratio	-0,0005	0,0004	0,0005	0,0003	-0,0006	0,0023	X	X	-0,0032	0,0044	0,0633	0,0380
EBITDA (M$)	-1,015E-06	8,555E-07	6,461E-6**	1,176E-06	-9,827E-07	6,539E-07	X	X	-1,900E-03	1,700E-03	-1,678*	8,492E-06
Dummy 2020 (COVID-19)	X	X	X	X	-0,2098**	0,0159	X	X	-0,0521**	0,0034	-0,2296**	0,0218
Level of EO	0,7456	0,9407	3,647**	1,0070	-0,9073	0,9228	0,8964	0,9460	-0,1924	0,2143	3,1149*	1,5544
Abruptness change EO	-12,757**	1,8848	2,2766	2,6965	1,8316	2,0354	-13,458**	1,8864	-2,0225**	0,4039	-13,287**	3,5935
Number of employees (*1000)	-0,0005	0,0003	-0,0001	0,0001	3,26E-05	0,0002	-0,0006*	0,0003	-0,0426**	0,0127	-0,0039*	0,0018
EO*EMP	0,0102	0,0067	0,0051	0,0089	0,0134*	0,0067	0,0086	0,0072	0,0110	0,0080	0,0443	0,0404
acEO*EMP	0,0212	0,0142	0,0127	0,0179	-0,0174	0,0152	0,0190	0,0144	0,0153	0,0109	-0,0180	0,0888
R-squared	0,0769		0,0604		0,2576		0,0640		0,3018		0,2950	
R-squared (Between)	-0,1213		0,0997		-0,4570		-0,0824		-0,8729		-0,5571	
R-squared (Within)	0,0769		-0,0651		0,2576		0,0640		0,3018		0,2950	
R-squared (Overall)	-0,0555		0,0450		0,0354		-0,0338		-0,4752		-0,1547	

*Firm fixed effects included; *p<0,05, **p<0,01*

Number of observations = 1040, Interaction terms are mean-centered

(a): 832 observation for 208 firms

(b): 664 observations for 161 firms

C3.1.2: Exclusion of outliers in Robustness model

For the identification of the outliers the interquartile range (IQR) was calculated for each of the variables. The IQR is the difference between the first and third quantile value. The IQR therefore measures the spread of the middle 50% of the variables. The lower and upper bound to determine the outliers were calculated with the following formulas:

$$Lower\ bound = Q1 - 1{,}5 * IQR$$

$$Upper\ bound = Q3 + 1{,}5 * IQR$$

With:

$$Q1 = quantile(0{,}25)$$

$$Q3 = quantile(0{,}75)$$

$$IQR = Q3 - Q1$$

All values that fall out of the lower and upper bound are labelled as outliers and were excluded in the robustness test model. The reason determine the outliers with this method is that it take the variable variance in consideration. The 1,5 is a common multiplier to use for the calculation of the lower and upper bound(Ben-Gal, 2005).

C3.2.1: Results manual time fixed effects estimation model

Table 12: Results time fixed effects manual

	Model 1		*Model 2*		*Model 3*		*Model 4*		*Model 5*		*Model 6*		*Model 7*	
	Coefficient	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**	**Coefficient**	**S.E.**
Intercept	3,8149	0,0265	3,7023	0,0426	3,7006	0,0425	3,7076	0,0431	3,7069	0,0428	3,7076	0,0431	3,7069	0,0429
Adjusted Tobin's Q	-0,0014	0,0094	-0,0026	0,0092	-0,0028	0,0092	-0,0026	0,0092	-0,0025	0,0093	-0,0024	0,0093	-0,0023	0,0093
Resource Slack	-0,0018	0,0107	-0,0051	0,0103	-0,0053	0,0102	-6,20E-03	0,0103	-0,0063	0,0103	-0,0062	0,0103	-0,0063	0,0103
Debt-to-Equity Ratio	0,0006	0,0003	0,0005	0,0003	0,0005	0,0003	0,0005	0,0003	0,0005	0,0003	0,0005	0,0003	0,0005	0,0003
EBITDA (M$)	5,68E-06**	1,06E-06	5,81E-06**	1,00E-06	5,87E-06**	1,01E-06	6,31E-06**	1,20E-06	6,38E-6**	1,18E-06	6,38E-06**	1,20E-06	6,46E-06**	1,18E-06
2017 Dummy	-0,0696**	0,0258	-0,0680**	0,0256	-0,0791**	0,0286	-0,0792**	0,0285	-0,0794**	0,0285	-0,0791**	0,0285	-0,0793**	0,0286
2018 Dummy	-0,1642**	0,0272	-0,1683**	0,0271	-0,1783**	0,0291	-0,1782**	0,0291	-0,1786**	0,0291	-0,1790**	0,0291	-0,1783**	0,0292
2019 Dummy	-0,3081**	0,0308	-0,3075**	0,0306	-0,3182**	0,0327	-0,3186**	0,0327	-0,3183**	0,0326	-0,3190**	0,0327	-0,3188**	0,0327
2020 Dummy	-0,3870**	0,0336	-0,3774**	0,0335	-0,3881**	0,0360	-0,3876**	0,0360	-0,3879**	0,0360	-0,3868**	0,0361	-0,3871**	0,0362
Level of EO	X	X	3,6428**	1,0045	3,6960**	1,0032	3,6530**	1,0074	3,6627**	1,0044	3,6373**	1,0101	3,6470**	1,0070
Abruptness change EO	X	X	X	X	2,2470	2,7053	2,2807	2,7018	2,2564	2,6985	2,3013	2,7016	2,2766	2,6965
Number of employees (*1000)	X	X	X	X	X	X	-0,0001	8,10E-05	-0,0001	0,0001	-0,0001	0,0001	-0,0001	0,0001
EO*EMP	X	X	X	X	X	X	X	X	0,0049	0,0088	X	X	0,0051	0,0089
acEO*EMP	X	X	X	X	X	X	X	X	X	X	0,0124	0,0179	0,0127	0,0179
R-squared	0,2035		0,2139		0,2145		0,2154		0,2155		0,2156		0,2158	
R-squared (Between)	0,4764		0,4547		0,4542		0,4509		0,4504		0,4498		0,4493	
R-squared (Within)	0,0678		0,0942		0,0953		0,0983		0,0988		0,0991		0,0997	
R-squared (Overall)	0,2035		0,2139		0,2145		0,2154		0,2155		0,2156		0,2158	

*Firm fixed effects included; *p<0,05, **p<0,01*

Number of observations = 1040, Interaction terms are mean-centered

C3.2.2. Analytical approach for time fixed effects

Table 13: Durbin-Watson test

		DW-statistic
Time Fixed effects	Model 1	0,784
	Model 2	0,806
	Model 3	0,806
	Model 4	0,808
	Model 5	0,809
	Model 6	0,810
	Model 7	0,811
Random effects	Model 1	1,767
	Model 2	1,757
	Model 3	1,756
	Model 4	1,755
	Model 5	1,756
	Model 6	1,755
	Model 7	1,756

Table 14: Hausman test

	Score	p-value
Model 1	20,92	0,013
Model 2	67,11	0,000
Model 3	69,33	0,000
Model 4	56,68	0,000
Model 5	61,37	0,000
Model 6	62,92	0,000
Model 7	68,71	0,000

Table 15: Breusch-Pagan test - Time FE

	Score	p-value
Model 1	7,77	0,000
Model 2	7,40	0,000
Model 3	6,51	0,000
Model 4	7,01	0,000
Model 5	6,37	0,000
Model 6	6,43	0,000
Model 7	5,88	0,000

Table 16: Shapiro-Wilk test - Time FE

	Score	p-value
Model 1	0,995	0,000
Model 2	0,996	0,000
Model 3	0,996	0,000
Model 4	0,995	0,000
Model 5	0,995	0,000
Model 6	0,995	0,000
Model 7	0,995	0,000

Table 17: VIF-scores for multicollinearity - Time FE

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	8,299	18,337	18,377	18,857	18,880	18,858	18,881
Adjusted Tobin's Q	1,071	1,074	1,074	1,075	1,076	1,078	1,079
Resource Slack	1,076	1,083	1,083	1,089	1,090	1,089	1,090
Debt-to-Equity Ratio	1,007	1,007	1,007	1,008	1,009	1,008	1,009
EBITDA (M$)	1,016	1,018	1,026	1,291	1,328	1,317	1,355
2017 Dummy	1,607	1,608	1,879	1,879	1,879	1,879	1,879
2018 Dummy	1,606	1,608	1,828	1,828	1,829	1,828	1,829
2019 Dummy	1,617	1,617	1,873	1,873	1,873	1,874	1,874
2020 Dummy	1,611	1,623	1,873	1,873	1,874	1,877	1,878
Level of EO	X	1,029	1,033	1,035	1,035	1,035	1,036
Abruptness change EO	X	X	1,263	1,263	1,263	1,263	1,264
Number of employees (*1000)	X	X	X	1,285	1,328	1,286	1,328
EO*EMP	X	X	X	X	1,122	X	1,123
acEO*EMP	X	X	X	X	X	1,032	1,033

EO = Entrepreneurial Orientation; acEO = Abruptness change EO

C3.3: Margin plots

Figure 24-27: Margin plots moderators on employee happiness