Norwegian School of Economics
Bergen, Fall 2020

Is Gender Equality Valued by Investors?

An event study of companies included in the Bloomberg Gender Equality Index

Thomas Nilsen and Petter Bruun

Supervisor: Kyeong Hun Lee

Master thesis, Economics and Business Administration

Major: Financial Economics

NORWEGIAN SCHOOL OF ECONOMICS

Acknowledgements

This thesis is written as a part of our Master of Science in Business Administration at the Norwegian School of Economics (NHH). It marks the end of our major in Financial Economics and, thus, two educational years at NHH. Throughout the rewarding process of writing this thesis, we have gained valuable experience that will benefit us when entering the financial job market.

We would like to thank our advisor, Associate Professor Kyeong Hun Lee, for constructive feedback and guiding us to find an inspiring topic.

Norwegian School of Economics

Bergen, December 2020

Thomas Nilsen

Petter Bruun

Abstract

This thesis investigates whether global markets value firm commitment to gender equality in the workplace by using event study methodology. We examine whether inclusion in Bloomberg's Gender Equality Index (GEI) yields abnormal returns and abnormal trading volume around the annual recomposition of the index. Hence, we study the effect GEI inclusion has on the full global sample and subsamples categorized by periods, geographical regions, and industries. Thus, allowing us to observe different market reactions to the respective subsamples over the past five years, starting in 2016, when the GEI was founded.

Contrary to our main hypothesis, which states that inclusion in the GEI should yield significant positive abnormal returns, this study's results do not yield any significant observations for the full sample around the annual recomposition over the period from 2016-2020. However, there seem to be differences between geographical regions. We observe significant positive abnormal returns the days following the announcement in the European region and significant positive abnormal returns the days prior to the announcement in the North American region. In contrast, the Asia-Pacific region yields no significant observations. Similar to the lack of abnormal return observations, this study does not find significant positive abnormal trading volume around the announcement except for on the day of the announcement, though the result is barely significant at the 10% level. Further, we cannot conclude that inclusion in the GEI differs between industries as we only observe significant abnormal returns around the announcement in one out of ten industries.

Our findings do not give sufficient support to conclude that investors value gender equality in the workplace on a global scale. However, the results indicate an increasingly positive view of gender equality over the years. From 2016-2018 we observe negative but not significant abnormal returns over the full event window. In contrast, the results in 2019 are positive and significant, and in 2020, the results remain positive but lose significance.

Contents

List of Figures

List of Tables

1 Introduction

This study aims to investigate whether inclusion in Bloomberg´s Gender Equality Index (GEI) yields abnormal returns and trading volume around inclusion in the index by applying the event study methodology. Inclusion in the GEI represents a firm´s commitment to transparency and excellence in gender equality reporting. By analyzing the effects of inclusion, this study examines whether global markets value gender equality in the workplace.

Positive abnormal returns following inclusion in an index are associated with an index effect. According to the efficient market hypothesis, stock prices reflect all available information about a company at any given time. Therefore, the index effect for a particular index can be analyzed by studying the impact index inclusion has on stock price and trading volume for companies included in the index around the annual recomposition.

By studying the full global sample over the period from 2016-2020, we do not find significant evidence to support the notion of an index effect associated with inclusion in the GEI. However, the results indicate an increasingly positive financial view of gender equality in the workplace throughout the years. By examining regional sub-samples, we find that the European and North American regions are positive to the news of inclusion while the Asia-Pacific region is neutral.

Structurally, this thesis first introduces the benefits of gender equality in the workplace, followed by an overview of the GEI and the required criteria for inclusion. The next section presents the literature review consisting of the academic framework and a review of previous studies. Further, we present our hypotheses, followed by the section describing the data used in this study and the process of cleaning said data. The following section validifies our empirical results' reliability by presenting the methodical approach used in this study. We then present the empirical results, followed by an interpretation of the findings. Finally, the last three sections present this study's conclusion, limitations, and suggestions for further research.

2 Gender equality and the GEI index

2.1 Gender equality

Gender inequality is a pressing matter, and it has never been more important for a company to show its commitment against this moral and social issue than it is today. With the increased focus on ESG in today's society, stakeholders now care more than ever about how companies treat their employees and contribute to society. McKinsey (2015) suggested that $12 trillion, or 26%, could be added to global GDP by advancing women's equality by 2025. Thus, there could be significant economic benefits for companies demonstrating a commitment to gender equality.

Furthermore, gender equality is a way of increasing diversity in the workplace. Diversity is proven to attract a greater range of talent, provide deeper insight, and make organizations more effective, successful, and profitable. More specifically, gender diversity fosters innovation as it increases collaboration between employees with different backgrounds and perspectives (Bloomberg, 2020c). According to Angela Sun, Head of Strategy and Corporate Development at Bloomberg, "Evidence demonstrates that gender-equality policies and practices can affect a company's financial performance, productivity and ability to retain top talent" (Bloomberg, 2016). Moreover, Dixon, Dolan, Hunt, and Prince (2020) argues that diverse companies are more likely to outperform and be more profitable than less diverse peers. Their analysis found that companies in the top quartile for gender diversity on executive teams were 25% more likely to have above-average profitability compared to companies in the fourth quartile. The higher the representation is, the more likely they are to outperform their peers.

Additionally, investment bank Morgan Stanley (2016) reported that companies who are more gender diverse than their peers offer similar returns but with lower volatility. Consequently, investors are actively trying to identify companies committed to addressing gender inequality. Hence, the demand for products where companies' can showcase their commitment has never been higher than in today's environment (Bloomberg, 2020c).

2.2 The GEI index

The Bloomberg Gender-Equality Index (GEI) is a market capitalization-weighted index that tracks the performance of public companies committed to supporting gender equality and transparency in gender-data reporting. The index provides an important opportunity for companies to attract new capital and investors as the demand for ESG products increase. Standardized disclosure of gender-related data allows companies to attract talent and enables employees and communities to hold companies accountable for progress (Bloomberg, 2020e). According to the founder of Bloomberg, Michael R.Bloomberg, "Promoting gender equality in the workplace is not just the right thing to do. It is also smart business" (Bloomberg, 2020e). After the launch of the index, there has been a significant improvement in gender reporting. The GEI provides "investors and organizations standardized aggregate data across company gender statistics, employee policies, gender-conscious product offerings, and external community support and engagement" (Bloomberg, 2016).

The index was founded May 3rd, 2016, and has a global perspective covering companies from all regions of the world. Today, the index consists of 325 companies with a combined market capitalization of $12 trillion across 11 industries in 42 different countries (Bloomberg, 2020a). Rebalancing for inclusion happens when the New York market opens on the Monday following the third Friday of January each year. Subsequent rebalancing occurs on the Monday following the third Friday of each of the three remaining quarters of the calendar year to account for market-cap changes. Companies included in the index stay constant throughout the year, except for companies excluded due to delisting or M&A's (Bloomberg, 2020d). In 2016 and 2017, the index only consisted of financial companies and was referred to as the Bloomberg Financial Gender-Equality index (BFGEI). In 2018 the index doubled in size as it expanded to cover all industries (Bloomberg, 2016). Furthermore, the index consists of large-cap companies who derive their revenues from the global economy. Bloomberg's GEI is a first-of-its-kind index in the marketplace for ESG information with individual data points related to gender equality and is only available through the Bloomberg Terminal (Bloomberg, 2020e).

2.3 Criteria for inclusion

To be included in the GEI, companies must commit to disclose their efforts to support gender equality through the Bloomberg Gender Reporting Framework. The framework is an international standardized reporting and disclosure method for workplace gender data and measures how companies promote gender equality over the following five dimensions:

- Female Leadership and Talent Pipeline.
- Equal Pay and Gender Pay Parity.
- Inclusive Culture.
- Sexual Harassment Policies.
- Pro-Women Brand.

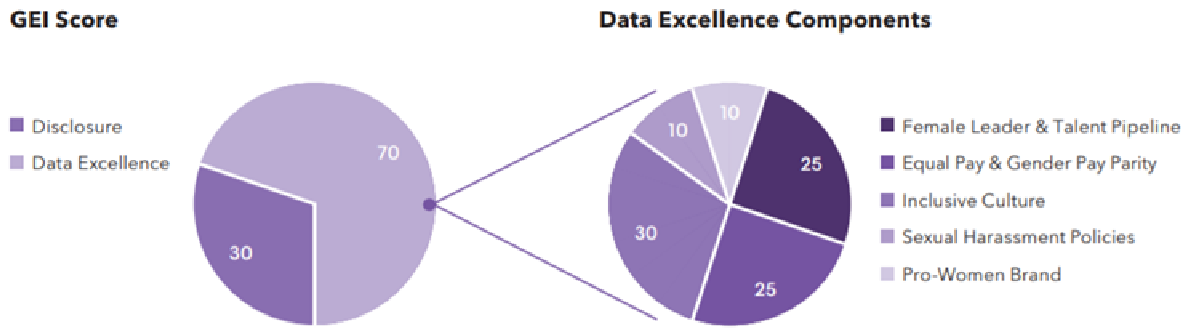
The reporting framework is designed in collaboration with leading gender-equality organizations and subject-matter experts. It is updated annually to ensure that it includes the most relevant metrics for promoting equality in the workplace (Bloomberg, 2020b).

Furthermore, a company can only be included in the GEI if it is publicly traded and has a GEI score above a global threshold established by Bloomberg. The GEI score is used as a metric to reflect levels of disclosure and overall performance across five dimensions, described in more detail in section 2.4 (Bloomberg, 2020b). A company must also meet the GEI universe criteria of current market capitalization greater than or equal to $1 B, a 3-month average daily value traded exceeding $50,000, and a 3-month average trading volume exceeding $5,000. (Bloomberg, 2020d).

2.4 The GEI score

The GEI score for each company is updated annually, as well as the threshold for inclusion. The Bloomberg GEI score measures a company's level of gender-related data disclosure and performance via a data excellence component score. Moreover, a company can get a GEI score between 0% and 100%, where 100% is the maximum score. Level of disclosure weighs 30%, while data excellence score weighs 70% of the overall GEI score. The data excellent component score is further broken down to scores over five dimensions, as seen in figure 2.1 below:

Figure 2.1: Composition of the GEI score



Note: GEI Score broken into disclosure and data excellence (Bloomberg, 2020d)

The five dimensions are weighted differently, and a company can score a maximum of 100% in each of the five dimensions. Inclusive Culture represents 30% of the overall score, while Equal Pay & Gender Pay Parity as well as Female Leadership & Talent Pipeline each represent 25%. Lastly, Sexual Harassment Policies and Pro-Women Brand represent 10% each (Bloomberg, 2020d).

3 Literature review

This section covers the literature review, presenting the academic framework that lays the foundation of our hypotheses and previous studies of the index effect performed on ESG indices. At the end of the literature review, we present our contribution to the existing literature.

3.1 Efficient market hypothesis

The efficient market hypothesis states that all available information about individual securities is incorporated in the security's price as observed in the market at any given time. Hence, the market is efficient (Fama, 1970). The efficient market hypothesis is based on the assumption of a *random walk*, where price changes occur from random departures from previous prices. Suppose the flow of information is not hindered, and new information is immediately incorporated in the price of a security. In that case, tomorrow's price change will be independent of today's price and will only reflect tomorrow's news. As news is unpredictable and random by nature, so will price changes be, and as a result, prices reflect all available information (Malkiel, 2003). Thus, trying to beat the market by speculating in stocks being overvalued or undervalued is useless. Since all relevant information and expectations of future performance are already reflected in the stock price, abnormal returns should not exist.

As defined by (Fama, 1970), the level of efficiency in a market can either be weak, semi-strong, or strong. The weak form of market efficiency solely incorporates historical information and implies that prices observed in the market reflect all historical information about specific securities. Thus, all investors have access to and can trade on the same information, and excess returns should not be obtainable. The semi-strong form of market efficiency incorporates both public and historical information in the price of a security, implying that fundamental and technical analysis will not yield excess returns. The only true way to beat the market is by trading on insider information not yet disclosed to the public. The final form is the strong form of market efficiency, which states that private, public, and historical information is already incorporated in the price of a security at any given time. Therefore, it is impossible to beat the market and obtain excess returns.

The efficient market hypothesis relies on a variety of assumptions on top of the *random walk* assumption. For there to be efficiency in markets, they need to be liquid and have rational investors who make good decisions about buying and selling stocks on average. New information also has to be free, simultaneously available, and similarly interpreted by investors. Thus, this study assumes that markets are efficient in the semi-strong form. Inclusion in the GEI should be viewed as new information to investors as Bloomberg is the exclusive holder of this information before the announcement of constituents. Hence, according to the efficient market hypothesis, the news should be incorporated into each security´s price within a few days.

3.2 Asymmetric information and signaling

Asymmetric information is the phenomenon that occurs when the two different sides of an economic transaction have different amounts of information about the product available. If the buyer had an equal amount of information about the product as the seller, the buyer would make more efficient decisions. The theory is most commonly referred to as the *lemon's principle* with the example of a used car dealership where the seller knows that the car's value is not as much as the value perceived by the buyer (Akerlof, 1970). This principle is well known in the financial industry as well, where the most common forms of asymmetric information are adverse selection, moral hazards, and monitoring costs.

Adverse selection occurs when a credit lender cannot distinguish projects with different levels of risk when allocating credit. Consequently, this leads to moral hazards. The borrower takes advantage of the credit lender's lack of information about the project and tries to hide the risk factors or allocate the lent money differently than previously stated. Furthermore, monitoring costs arise from moral hazards and refers to borrowers' hidden actions, most typically when they take advantage of lenders' lack of information and declare lower earnings than the real earnings (Bebczuk, 2003).

Asymmetric information was a crucial factor in giving rise to financial intermediaries, to efficiently produce information in environments where borrowers have private information about their investment opportunities (Boyd & Prescott, 1986). Today, such intermediaries are seen worldwide as credit rating agencies, financial banks, and various analyst agencies trying to decrease asymmetric information between buyers and sellers of financial products.

Moreover, some companies commit to disclosing their CSR practices to be seen as socially responsible while hiding irresponsible behavior in their core business. Consequently making it harder for investors to assess a firm's social responsibility practices (Doane & Abasta-Vilaplana, 2005). ESG indices such as the GEI make CSR information more transparent to investors and make it easier to invest in firms committed to CSR. Thus, if investors value gender equality, an increase in firm value should be observed around the announcement of constituents. Consequently, inclusion in the GEI reduces information asymmetry about gender equality between firms included in the index and potential investors. Furthermore, investors rely on these ESG indices when investing as a source to reduce information asymmetry when looking for socially responsible investments. High ESG rated companies are typically more transparent, particularly concerning risk and how they manage their risk (Giese, Lee, Melas, Nagy, & Nishikawa, 2019).

Signaling is the most common way to deal with asymmetric information. Financial instruments can help reduce information asymmetries by signaling the firm's true value to the market without moral hazard or disclosure of confidential information (Talmor, 1981). The theory was first introduced by Spence (1973), who analyzed the job market from an employee's perspective. In simple terms, by sending signals to the market, an unemployed person has a potential advantage over others who are unemployed by broadcasting their talents to the public, attempting to attract employers' attention.

In signaling theory, there are two counterparts: the signaler and the receiver. The signaler (usually an executive or manager) sits on information that is not publicly available, while the receivers are those in the market that would potentially benefit from the insider information. Insiders obtain both positive and negative private information and make decisions on whether to communicate this information to the public or not. A signal is defined as a form of "communicating positive information in an effort to convey positive organizational attributes" (Connelly, Certo, Ireland, & Reutzel, 2011). Further, signals need two attributes to be efficient: observability and cost. Signal observability refers to the extent outsiders can notice the signal. If the actions insiders take are not easily observed by receivers, the actions are difficult to communicate. Signal cost refers to the fact that some signalers are more capable of absorbing the associated costs than others. Certain signals, such as getting certifications, might be time-consuming and costly, allowing larger and more profitable firms to send signals which their less profitable competitors cannot afford (Connelly et al., 2011).

Regarding our study, even though a company's inclusion in the GEI does not directly induce any financial gains, the inclusion signals a strong commitment to CSR. This commitment is proven to benefit a company in the long run with regards to cost of capital and future performance (McGuire, Sundgren, & Schneeweis, 1988). If our hypotheses hold, and the market values gender equality, the signal from inclusion in the GEI should ultimately lead to an increase in price as the market adjusts to the new information.

3.3 The index effect and hypotheses explaining the index effect

The index effect is often used to explain abnormal returns around index inclusion(exclusion), and several studies from the past have studied the effect (see section 3.5). During the immediate days surrounding the event, the securities experience positive or negative abnormal returns or excessive changes in trading volume. Several hypotheses attempt to explain this phenomenon, and this thesis will cover the most relevant ones regarding ESG and the GEI.

3.3.1 Price pressure

The price pressure hypothesis was proposed by Scholes (1972) and Kraus and Stoll (1972). They suggest that the demand and trading volume for securities increase rapidly close to the inclusion date, causing prices to diverge from its information-efficient values. Moreover, the hypothesis assumes that the index inclusion holds no new information in itself. The price increases as shareholders are compensated for the transaction costs and portfolio risk they bear when they provide liquidity due to the demand shift. This compensation occurs over a short time horizon before prices return to their information-efficient values. Harris and Gurel (1986) might bring the most convincing evidence of price pressure, estimating that firms added to the S&P 500 index earn as much as 3% abnormal return at the inclusion date. The authors argue that inclusion to the S&P 500 provides no new information but is caused by increased demand by investors tracking the S&P 500. Thus, the validity of this hypothesis regarding increased demand for securities in the GEI is conditional on that a considerable number of investors track the index.

3.3.2 Awareness

The awareness hypothesis was proposed by Goetzmann and Garry (1986) and assert that stocks listed in an index receive more attention than their non listed peers. In other words, investors invest in stocks that are known to them. According to Merton (1987), investors bear so-called shadow-cost which is a product of information costs due to incomplete information. Consequently, searching cost increases due to shadow-cost, which again increases trading costs. However, when a stock is included in an index, like the GEI, shadow-cost will decrease and add value for the investor. This increase in value should be observed through the increased price and trading volume at the inclusion date as long as there is no information leakage. Otherwise, it should be observed during the days before the inclusion.

3.3.3 Imperfect substitutes and the downward sloping demand curve

Scholes (1972), Kraus and Stoll (1972), and Hess and Frost (1982) propose the imperfect substitutes hypothesis. The hypothesis assumes that investors perceive each stock as a unique asset without perfect substitutes for each other. Therefore, investors will select securities based on their characteristics and their individual preference and needs. Hence, the value of a stock will depend on supply and demand. Under this hypothesis, the demand curve will be downward sloping, in contrast to a horizontal demand curve. A stock's value will not depend on supply and demand if securities have perfect substitutes.

The downward sloping demand curve mentioned above is a hypothesis that was articulated by Shleifer (1986). Under the conditions of a downward sloping demand curve, the stock price is sensitive to shocks in demand. If the demand for a stock suddenly increases (decreases), the price will increase (decrease) to a new equilibrium. Consequently, if a stock is added to an index, one could expect a permanent price increase as investors reweight their portfolios and react to index changes. More specifically, concerning a GEI inclusion, investors who actively seek gender-diverse companies obtain lower volatility at the same return rate. Investors would reweight their portfolios when inclusion and rebalancing occur in the index, as previously suggested by investment bank Morgan Stanley (2016).

3.3.4 Information cost/liquidity

Barry and Brown (1985) and Amihud and Mendelson (1986) were the first to present the information cost/liquidity hypothesis. The hypothesis was later supported by Beneish and Gardner (1995), who found evidence that investors demand a premium for investing in securities with less information available and low liquidity. The rationale behind this hypothesis is that low liquidity increases bid-ask spreads, and less information increases transaction costs as gathering information is a costly process. If a stock is included in a reputable index, analyst coverage will increase, providing more information to the public. Hence, this increase of information flow attracts new investors, leading to increased liquidity and trading volume, which effectively reduces the bid-ask spreads. Concerning inclusion in the GEI, 30% of the GEI score is determined by the level of disclosure on gender-related data. Thus, at the GEI's inclusion date, one could expect a lower risk premium and a permanent increase in price and volume due to the increased information available.

3.3.5 Information signalling

Ross (1977), Mikkelson (1981), and Jain (1987) presented the information signaling hypothesis in their study on how stock returns react to signals sent and absorbed by the market. If the signals are positive (negative), the stock price will increase (decrease). Their study applies to index inclusion (exclusion) as these events can be perceived as private information released by an index provider to the market. Thus, these events can produce strong signaling effects regarding a company's level of corporate social performance. Information signaling especially applies to inclusion in the GEI as Bloomberg releases private information on gender-related data. If a stock is included in the GEI, it should be perceived as a positive signal, and the price should increase, while an exclusion should be perceived as a negative signal, and the price should decrease. As discussed earlier, inclusion in the GEI will signal exceptional transparency in gender-related data disclosure and excellent scores across the five dimensions measured. Lastly, the hypothesis articulates that the price increase from signaling will be permanent.

3.3.6 Corporate sustainability taste

Cheung and Roca (2013) developed the corporate sustainability taste hypothesis and proposed that investors may have a taste for sustainable firms on different grounds like morality, religion, and loyalty. The hypothesis introduces additional utility for investors with taste or preferences for sustainable firms from holdings these shares on top of their utility from returns on these shares. This additional utility or "taste" for sustainable corporations implies that prices of these securities will increase/decrease when they are included/excluded in a sustainability index. Thus, we expect to see an increase in share price and trading volume when a stock is included in the GEI if investors track the index or the corporations included.

3.3.7 Sustainability redundancy

Cheung and Roca (2013) also introduce a second hypothesis, the sustainability redundancy hypothesis. This hypothesis is somewhat the opposite of the sustainability taste hypothesis. It articulates that by selecting stocks based on corporate sustainability, investors are not creating optimal portfolios based on risk minimization and return maximization. Instead, they are adding additional (redundant) constraints on portfolio optimization. Thus, by creating suboptimal portfolios, this hypothesis implies that index inclusion in a sustainability index is associated with negative abnormal returns and increased trading volume as inclusion is perceived as a negative signal.

3.4 Corporate social responsibility, cost of capital and financial performance

The positive relationship between ESG and corporations' financial performance, primarily focusing on a company's commitment to Corporate Social Responsibility (CSR), has received increased attention and focus over the past two decades. A report from the UN (2004) stated that 20 of the largest and most influential international financial agencies view ESG scores as a positive and critical factor of a firm's strategy and management.

Similar to our study of gender equality reporting and firm performance, Arayssi, Dah, and Jizi (2016) investigated the role of women directors on corporate boards in sustainability reporting and shareholder performance. The study included a selection of firms in the Financial Times Stock exchange 250 index between 2012 and 2017. They found that the presence of women directors on corporate boards positively affects the firm's risk and performance and is viewed as an opportunity to invest in social engagement.

Friede, Busch, and Bassen (2015) reviewed 2200 research papers on the relationship between ESG and financial performance. Approximately 90 percent of the studies showed a positive or neutral relationship between ESG and corporations' financial performance, making a robust case for ESG investments. Additionally, De Lucia, Pazienza, and Bartlett (2020) recently studied 1038 companies in Europe from 2018-2019 and compared ESG scores to financial metrics such as ROE and ROA. They found that most public companies exhibit a positive relationship between ESG and financial performance. Moreover, Nordea (2017) studied the European market and found that from 2012-2015, the highest ESG rated companies outperformed the lowest ESG rated companies by up to 40%.

Furthermore, a report by Fulton, Kahn, and Sharples (2012) found that companies with high CSR scores within the ESG factors have a lower cost of capital in terms of debt and equity. Thus, the market recognizes that these companies have lower risk than other companies and reward them accordingly. Moreover, Jiraporn, Jiraporn, Boeprasert, and Chang (2014) found that firms with better CSR scores obtain higher credit ratings and lower credit spreads, thus decreasing the cost of debt. Giese et al. (2019) further found evidence that ESG scores lead to higher valuations. As companies with high ESG scores are considered less risky to investors, they experience lower systematic risk (beta), which leads to lower required rates of return. With the lowered cost of debt and equity, the overall cost of capital is decreased.

When valuing a company either with the free cash flow model or the dividend discount model, a company's value is the future cash flows or dividends discounted back to the present by the cost of capital. Thereby, if high ESG scores correlate with a lower cost of capital, it will increase the company's valuation. The common assumption that investors are risk-averse further backs this notion. As companies with low ESG scores are considered less transparent and riskier, they will experience a smaller investor base. In contrast, companies with high ESG scores are considered more transparent and less risky. Therefore, they will attract a larger investor base as investors are actively looking for investments with lower risk (Giese et al., 2019). Thus, if investors view inclusion in the GEI to be a signal of increased CSR and infer less risk related to the company, the required rate of return should decrease. Hence, according to the efficient market hypothesis, the observed market price of the security should increase once the information becomes available.

3.5 Previous studies on ESG index inclusion:

Over the last decade, there has been an exponential increase in the interest of ESG and companies that show commitment to CSR by being transparent with their practices. Thus, giving investors more insight into which companies allow them to invest socially responsibly. This increased attention to environmental, social, and corporate governance practices has led to an increase in indices composed only of companies with high acknowledged standards for the three components of ESG. These ESG indices work as intermediaries between the companies included in the indices and investors. The indices represent independent and neutral third-parties, saving investors the time and cost of researching companies' ESG practices individually. Inclusion or exclusion from an ESG index sends direct signals to investors that a company has excelled in one of these fields and is getting acknowledged for it. Or that a company has failed to meet its expected high performance within the fields of ESG and does not meet the criteria threshold for inclusion.

The consensus that ESG is valuable in the long term is increasing. As ESG indices have entered the global spotlight, multiple studies to measure the effect inclusion or exclusion from such an index can have on stock prices have been conducted. Most of the historical index effect studies done on ESG indices have focused on CSR. The studies vary concerning time periods, event windows, regions, sample sizes, applied methodology, and differing positive and negative abnormal return observations with varying significance levels.

Consolandi, Jaiswal-Dale, Poggiani, and Vercelli (2009) conducted a study on the effect announcement of inclusion and exclusion in the Dow Jones Sustainability (STOXX) index (DJSSI) had on the European stock market from 2002 – 2006. Their study was conducted using an event window spanning 10 days before the announcement to 10 days after the effective date to capture both the anticipation effect and post-effect. The results yield positive abnormal returns for inclusions in the index, with abnormal returns increasing from the pre-announcement up until the effective date, after which it declines. For exclusions, negative abnormal returns are observed from the announcement to after the effective date. The authors find a positive anticipation effect connected to continuation in the index, as the excluded companies experience positive abnormal returns leading up to the announcement. Additionally, they find that the market seems to punish deletion from the index more than it appreciates inclusion. Most likely, investors' expectations of continued high CSR standards are already incorporated in the stock price. These price-incorporated expectations cause included companies to experience lower positive abnormal returns. On the other hand, exclusions from the index are more heavily punished in response to the unexpected decrease in sustainability standards. The study finds that included companies experience positive abnormal trading volume over the event window, while excluded companies do not.

Cheung (2011) evaluated the impact of inclusion and exclusion for US companies in the Dow Jones Sustainability World Index (DJSWI) from 2002-2008. The author studies abnormal return, trading volume, and risk. The results indicate an anticipation effect for inclusions as abnormal returns increase from negative values a few days before the announcement but lose momentum after that. On the other hand, abnormal returns for stocks excluded from the index decrease and become negative a few days after the announcement. The author finds negative abnormal trading volumes for inclusions the days after the announcement and positive abnormal trading volumes after the effective date. Similar abnormal volume results are found for stocks excluded from the index. The results show no change in systematic risk for either included or excluded companies, but companies excluded from the index experience increased idiosyncratic risk.

Gladysek and Chipeta (2012) examined abnormal returns around the announcement of inclusion to the Johannesburg Stock Exchange Socially Responsible Index (JSE SRI) from 2004-2009. The authors use a 41-day event window, starting 20 days before the announcement to 20 days after. The study finds varying signs of abnormal returns over the period, with 2005 being the only year with significant results observing increasingly positive abnormal returns over the full event window.

Lackmann, Ernstberger, and Stich (2012) examined the market reaction to inclusions in the DJSI STOXX in Europe from 2001-2008 using a 21-day event window. The authors argue that inclusion in an ESG index does not provide any new information in itself. Most companies publicly disclose their CSR practices to promote their commitment to CSR or divert the public's attention away from less ethical corporate practices. Thus, making it hard for investors to financially assess the disclosed information. As information needs to be both relevant and reliable to be of value to investors, the authors argue that ESG indices work as mediators to promote the information's reliability. Further, they propose the "Increase in information reliability hypothesis" to explain the market reactions to inclusion or exclusions from ESG indices. The study yields significant positive abnormal returns from inclusion over the whole event window, with no observed volume effect. Furthermore, the results show that idiosyncratic risk and leverage affect the degree inclusion has on a company. Higher levels of idiosyncratic risk and leverage increase the effect of index inclusion.

Nakai, Yamaguchi, and Takeuchi (2013) studied the effect announcement of inclusion and exclusion from the Morningstar Socially Responsible Investment Index (MS-SRI) had on Japanese stock prices from 2003-2010. The authors argue that the results observed give a better measurement of how Japanese investors react to CSR since it is a relatively new concept to the Japanese market. The index consists of companies varying in size, with firms selected from a social screening of 3600 companies. Further, they argue that other ESG indices are composed of companies based on their ESG score and their economic strength. Therefore, biased results might occur when studying these indices as investors might be reacting to the economic valuation criteria instead of the social responsibility criteria. For the announcement of included companies, the study finds that abnormal returns are significantly positive in 2006 and 2007, and significantly negative in 2003, 2004 and 2008 (possibly due to the financial crisis). Regarding exclusions from the index, 2004 is the only year that yields statistically negative returns around the announcement. As inclusions are more awarded than exclusions are punished, the results suggest that Japanese investors do not expect firms to practice CSR but appreciate those that do.

Cheung and Roca (2013) conducted a similar event study of the DJSI World as the study conducted by Cheung (2011), focusing on the Asia-Pacific region from 2002-2010. This study yields similar results, with no change in systematic risk, but both included and excluded companies experience increased idiosyncratic risk. Both included and excluded companies experience negative abnormal returns and an increased trading volume around the announcement and effective date. The findings of this study imply that the Asia-Pacific region views ESG in a negative manner. The authors describe this effect with the sustainability redundancy hypothesis. The hypothesis implies that ESG negatively affects firm value as corporate sustainability is equivalent to imposing additional or redundant constraints on a firm, thereby reducing portfolio optimization.

Kappou and Oikonomou (2016) conducted an event study on two of the oldest and well-known US SRI indices; The Calvert Social Index and the MSCI KLD 400 Social Index (formerly known as the Domini 400 Social Index). The authors examine abnormal returns and trading volume over the entire life of the two indices. The Calvert Social Index is studied from 2000-2011, while MSCI KLD 400 is studied from 1990-2010. The event window starts 15 days before the event and ends 125 days after, to capture the long-term effect. The Calvert index yields positive abnormal returns the days leading up to the event for the included companies, but negative returns from the event date to the end of the event window. The companies excluded from the index experience positive abnormal returns around the event but none of the Calvert observations are statistically significant. Furthermore, the Calvert also fails to show any statistical significance when it comes to abnormal trading volume of either included or excluded stocks. The MSCI KLD 400 yield similar abnormal return results around the event, but the excluded companies' long-term performance shows a significant negative abnormal return of 14%. Moreover, exclusions from the MSCI KLD 400 show statistically positive abnormal trading volumes from 10 days prior, to 5 days after the event.

Joshi, Pandey, and Ros (2017) evaluated the stock market reaction to US firms entering or leaving the DJSI from 2002-2011. The authors argue that previous literature has treated the effects of DJSI inclusion or exclusion as symmetrical but opposite in direction where inclusions are value-adding, and exclusions are value-destroying. The authors disagree, stating that firms included in the index have already incurred the cost of a sustainable reputation. Thus, the associated costs and benefits are already incorporated into the stock price. Exclusion from the index implies that the company will be unable to reap the potential future benefits from the investment of obtaining such a reputation.

Therefore, the exclusion is viewed as a sunk cost, and investors perceive exclusion mostly as a failed strategy or investment. As a result, the stock market will react negatively to exclusions regardless of their initial reaction to the inclusion in the DJSI. The results yield that exclusions from the index are viewed non-positively and that the market generally reacts negatively to a firm's inclusion in the DJSI. Investors view inclusion as value-destroying due to the additional constraints on production technology and over-compliance. Consequently, it results in a competitive disadvantage, aligning with Cheung and Roca (2013) sustainability redundancy theory.

Hawn, Chatterji, and Mitchell (2018) conducted a more complex longitudinal event study on the DSJI world. The study covers inclusions, exclusions, and continuations of stocks in the index from 27 countries over 17 years from 1999-2015. The authors argue that previous event studies on ESG indices suffer from empirical limitations. These limitations include that most of the studies do not examine abnormal returns of stocks that experience continuation in the index. Further, no comparison of abnormal returns of similar stocks that are not in the index are made, and short time horizons fail to capture investors reaction to sustainability over time. The samples are also often limited to single regions, and there is often a lack of control for other sources of heterogeneity. By including comparison groups of firms that continue in the index with observationally equivalent firms that are not affected by DJSI announcements, conclusions can be drawn about investor reactions over time. The results of the study yield that there has been an increase in the valuation of sustainability over time. Globally, the stocks affected by the index show little difference to their observationally equivalent stocks after relevant controls and comparisons are made, indicating that investors are neutral to DJSI announcements. In the US, the reactions to the effects of the index have been decreasing but with increasing benefits for those stocks with long-term continuation in the index. The results suggest that companies may at least gain limited benefits from the continuation of reliable sustainability practices.

J. W. Park and Lee (2018) examined abnormalities in stock return, and volume traded concerning inclusion and exclusion from the Korean SRI Governance Index from 2003-2012. The authors aim to examine the price pressure, information, liquidity, and downward sloping demand curve hypothesis. The study concludes that inclusion in the SRI Governance Index yields positive abnormal returns in the Korean stock market, while exclusions yield negative abnormal returns. The positive abnormal returns from inclusion change from positive to negative in the short run, which might be associated with momentary price pressure. Therefore, the authors' partly accepts the price pressure hypothesis. In the short term, stock prices temporarily decrease, followed by an increase throughout the long-term performance. The results show that the new information affects firm value, and thereby, the information hypothesis is accepted. The downward sloping demand curve hypothesis is also accepted as both short-term and long-term stock performance experience positive abnormal returns. Thus, the number of stocks available in the market decreases, causing the supply line to shift to the left-hand side with a decreasing demand curve. Finally, the liquidity hypothesis is partly accepted as volume traded during the event window is partially higher than the expected volume.

Zou, Wang, Xie, and Zhou (2019) conducted an event study of abnormal returns in the three emerging markets of China, Brazil, and South Africa. The study researches the effect of inclusion in pioneering SRI indices in the respective countries over a short event window of 7 days around the announcement. In 2009, China launched two SRI indices. The SSE Social Responsibility Index and SZSE CSR Price Index, on the Shanghai and Shenzhen stock exchange, respectively. In 2004, the SJE Socially Responsible Investment Index was launched on the Johannesburg Stock exchange, and in 2005, the Brazilian Corporate Sustainability Index (BSCI) was launched on the BM&FBOVESPA stock exchange. The study examines each index from launch until 2017. When computing the results, the authors combine the sample of companies from Brazil and South Africa and present them as one sample. The Chinese sample yields positive abnormal returns over the entire event window, while the combined Brazil and South Africa sample only exhibit significantly abnormal returns post announcement. The authors further examine the level of influence inclusion in an SRI Index has on the observed abnormal returns by incorporating control variables. They find that positive financial reaction to the announcement of inclusion to an SRI index is heightened by R&D expenditures and weakened by advertisement expenditures. Further, the reaction is stronger for firms that have expanded globally to other developing countries rather than to developed countries. The findings imply that investors in emerging markets reward those firms that contribute to other developing countries when evaluating firms' CSR performance.

Summing up, there seems to be a wide variety in the findings of the previous studies. This is not unexpected as the previous studies are conducted in different time periods, with differing applied methodologies. The samples are also extracted from different regions with different indices being studied. The different results suggest that CSR is viewed as a financial constraint in some regions and value increasing in other regions, where investors increasingly value CSR over time.

The studies find that CSR is most highly valued in Europe and least valued in the Asia-Pacific region according to the findings of Cheung and Roca (2013). Although, for the Asian countries Japan and Korea, Nakai et al. (2013) and J. W. Park and Lee (2018) find indication that CSR is becoming increasingly valued by investors, which is backed on a global level by the findings of Hawn et al. (2018). Further, US reactions to stocks affected by ESG indices are diminishing, and investors show neutrality to inclusions, possibly due to firms' existing expectance to deliver on CSR criteria. The existence of continuing CSR expectations in the US is a valid assumption as exclusion from indices are more heavily punished than inclusions are rewarded.

The aforementioned studies on ESG indices are conducted on indices where companies are included based on their CSR on various measurements. This study aims to differentiate itself from the previous studies by employing the theories to a first-of-its-kind gender equality index with extremely specific CSR requirements for inclusion. To our knowledge, this has never been done before.

3.5.1 Summary of previous studies

Table 3.1: Summary of previous studies

Authors	Index	Region	Summary
Consolandi et al. (2009)	DJSI STOXX	Europe 2006-2010	Positive AR increasing from AD to ED for inclusions. Positive AR until AD for exclusions, negative AR post-AD. Inclusions experience AV over event window, no AV observations for exclusions.
Cheung (2011)	DJSI WORLD	US 2002-2008	AR for inclusions increase from negative values before AD then loses momentum. Exclusions experience negative AR after AD. Negative AV for both inclusion and exclusion around AD, positive AV for both inclusion and exclusion after ED.
Gladysek and Chipeta (2012)	JSE-SRI	South Africa 2004-2009	Positive AR pre-AD throughout event window in 2005. No significant observations other years.
Lackmann et al. (2012)	DJSI STOXX	Europe 2001-2008	AR for inclusions over the whole event window. Companies with higher levels of idiosyncratic risk or leverage are more affected by index inclusion.
Nakai et al. (2013)	MS-SRI	Japan 2003-2010	AR for inclusions shifts from negative in 2004 and 2005 to positive in 2006 and 2007. Valuation of CSR increasing over time. Negative AR in 2008 possibly due to financial crisis. No significant effect for exclusions.
Cheung and Roca (2013)	DJSI WORLD	Asia-Pacific 2002-2010	Negative AR and positive AV for both inclusion and exclusion of stocks around AD and ED. Both inclusions and exclusions experience increased idiosyncratic risk. ESG is viewed in negative manner.
Kappou and Oikonomou (2016)	Calvert/ MSCI KLD 400	US 2000-2011/1990-2010	No significant AR or AV observations for Calvert. Negative AR in long-term for companies excluded from KLD 400. Positive AV around ED for exclusions from KLD 400.
Joshi et al. (2017)	DJSI WORLD	US 2002-2011	Inclusions are viewed negatively as investors view ESG as constraints and competitive disadvantage. Exclusions are viewed as non-positive. Results align with Sustainability redundancy theory.

Hawn et al. (2018)	DJSI WORLD	Global 1999-2015	Limited effect from inclusion, exclusion or continuation on indexes after comparisons to equivalent stocks are made. Increased valuation of CSR globally over time. US shows decreasing reaction to index effect over time.
J. W. Park and Lee (2018)	Korean SRI	Korea 2003-2012	Positive AR for inclusions up until AD, followed by negative AR post AD which then turn positive again. Negative AR for exclusions. CSR viewed as positive in Korea.
Zou et al. (2019)	SSE-SRI/SZSE-CSR/SJE-SRI/BSCI	China 2009-2017/South-Africa 2004-2017/Brazil 2005-2017	Positive AR for inclusion in China over event window. Positive AR for inclusion in combined South Africa / Brazil sample post-AD. Findings imply investors from emerging markets reward firms that contribute to other emerging countries.

Note: The table summarizes previous studies on ESG index inclusion. AR/AV denotes abnormal return and abnormal volume, while AD/ED denotes the announcement date and effective date.

4 Hypotheses

This thesis aims to capture the effect GEI inclusion has on stock performance around the annual recomposition of the index. Our study is based on the belief that investors value gender equality. Therefore, companies included in the GEI should experience abnormal returns and trading volume around the announcement of inclusion. Should the efficient market hypothesis hold, the information should be incorporated in the stock price immediately following the announcement. Further, this thesis will not study exclusions from the GEI because of the low sample size available due to confounding events during the event windows of interest.

According to the price pressure and awareness hypotheses, abnormal returns and trading volume should be observed around the announcement. The hypotheses state that demand and trading volume should increase rapidly, causing the stock price to increase to a new equilibrium. The effects are caused by investors rebalancing their portfolios and by the market becoming increasingly aware of the companies that excel in the field of CSR and gender equality compared to their peers. Thus, increasing value by reducing information asymmetries and searching costs, which attracts new investors. Furthermore, the information signaling and liquidity hypothesis also suggest increased abnormal returns and trading volume. Inclusion in the GEI should be viewed as a positive signal by the market. Releasing this private data should increase the stock price as it attracts new investors, leading to increased trading volume and therefore increased liquidity.

The imperfect substitutes hypothesis state that investors perceive each security as a unique asset without perfect substitutes. Therefore, investors will select stocks based on their characteristics and individual preferences, such as gender equality. Thus, the stock price will depend on supply and demand, increasing/decreasing as demand increases/decreases. If there are no perfect substitutes for an individual stock, the demand curve will be downward sloping. Suppose there is a downward sloping demand curve due to imperfect substitutes. In that case, the downward sloping demand curve hypothesis articulates that stock prices will be sensitive to shocks in demand. Consequently, if the demand for a stock suddenly increases due to inclusion in the GEI, the price should also increase until it reaches a new equilibrium.

The literature shows an increasing financial optimism trend toward CSR, which we believe is true. With a sample from a more recent time horizon than the literature, and the index effect hypotheses as a foundation, we present our first hypotheses:

Hypothesis 1: GEI inclusion yields significant positive abnormal returns.

Hypothesis 2: GEI inclusion yields significant positive abnormal trading volume.

Differing from the majority of ESG indices, the GEI announces and recomposes the index on the same date without a period in between. Therefore, we examine if there are abnormal returns and trading volume prominent before the announcement to control for information leakage. Thus, we present our third hypothesis.

Hypothesis 3: There is information leakage prior to the GEI inclusion date.

Further, the corporate sustainability taste and sustainability redundancy hypotheses are two more recent index effect hypotheses that contradict each other regarding how investors view CSR. According to the corporate sustainability taste hypothesis, investors value CSR on grounds such as morality and perceive additional utility by holding these stocks in their portfolio. Thus, inclusion in an ESG index, such as the GEI, should increase the stock price and trading volume. On the other hand, according to the sustainability redundancy hypothesis, CSR adds constraints on firms that will inhibit value maximization. Therefore, stock price should decrease as including firms listed in the GEI in a portfolio would create a suboptimal portfolio.

The notion that investors view CSR differently is backed by the existing literature findings, which show that the effect of inclusion in an ESG index differs between geographical regions. As this study is performed on a global sample, similar observations are expected. Further, as a contribution to the literature, this study will also examine if the effect of GEI inclusion differs between industries. Thereby, we present our two final hypotheses:

Hypothesis 4: Effect of GEI inclusion differs between geographical regions.

Hypothesis 5: Effect of GEI inclusion differs between industries.

5 Data

5.1 Databases

The empirical analysis is conducted using R (Rstudio). Historical data on index inclusions is retrieved from Bloomberg's official website. Further, data on confounding events are checked through the Bloomberg terminal ("company events" function), where each company is checked separately. Historical stock closing prices, trading volume, and index prices are retrieved from the financial database Datastream. Yahoo Finance is used to cross-check data. Lastly, stock prices are obtained through a total return index to adjust for dividend payments and stock splits.

$$RI_t = RI_{t-1} \cdot \frac{PI_t}{PI_{t-1}} \cdot (1 + \frac{DY_t}{100} \cdot \frac{1}{N}) \tag{5.1}$$

RI_t and RI_{t-1} is the total return at time t and t - 1. PI_t and PI_{t-1} is the price at time t and t - 1. DY_t is the dividend yield % at time t and N is the number of working days in the year (Datastream, 2020).

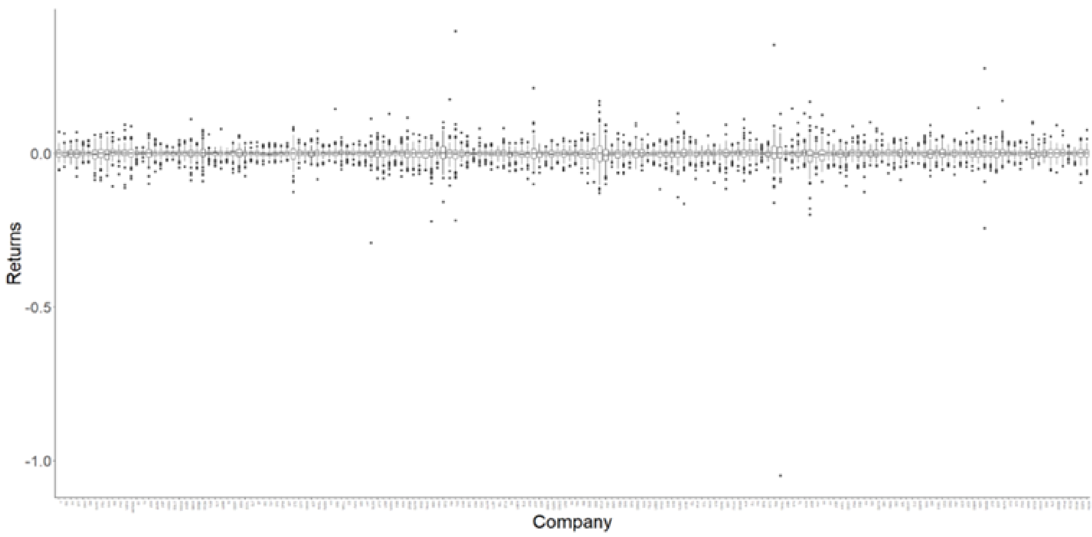
5.2 Data selection and pre-processing

In terms of data selection, we have 5 years of data from 2016 to 2020. Since the index was first founded as a gender-equality index for financial institutions and later expanded to cover all industries, the majority of the sample consists of companies from the financial industry. Each event is defined by a company's inclusion in the index, which happens in the first quarter each year, except for 2016, since the index was founded in May.

Furthermore, regions with a low sample size are removed from the total sample, i.e., securities from Africa and South America. Afterward, companies with any confounding events in the event window are removed from the sample as they could bias the results. Confounding events makes it difficult to interpret whether the market reacts to the GEI inclusion or the confounding event itself. In this study, confounding events are defined as any event that could contaminate the returns, such as earnings announcements, announcements of dividend changes, issuance of guidance, or other company related confounding events. Finally, securities with no daily trading volume are omitted from the sample as they do not have sufficient data.

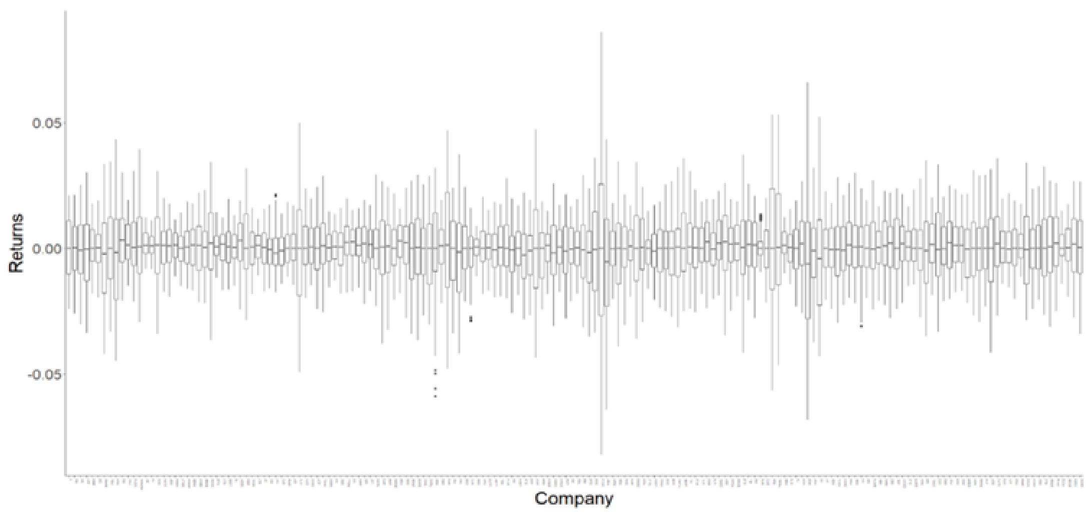
Thereafter, the estimation data is treated for outliers by winsorizing at the 5th and 95th percentiles. Outliers in the estimation sample will bias the OLS forecast of abnormal returns and thus reduce the validity of the CAAR test statistics as their variance would be inflated (Mills, Coutts, & Roberts, 1996). Winsorizing reduces the influence of extreme values by converting all values above/below a cut-off point to the actual cut-off point. In other words, the most extreme values are replaced with less extreme values.

Figure 5.1: Outliers before outlier treatment



*Note: Boxplot of raw data where each dot represent an outlier. The box is the interquartile range (IQR) equal to Q3 minus Q1, while the maximum and minimum bound is Q3+1,5*IQR and Q1-1,5*IQR*

Figure 5.2: Outliers after outlier treatment



Note: Boxplot of winsorized data at the 5th and 95th percentiles.

The next step in the pre-processing part is to treat missing values in the data set due to national holidays or other country-specific events. Hence, all rows with missing values are omitted. The disadvantage of this approach is that it can lead to bias in the data as we remove multiple rows that could contain valuable information for prediction.

Lastly, as this study goes across multiple countries and regions in different time zones, trading hours will not overlap. Therefore, investors can not react simultaneously to new information (N. K. Park, 2004). There is about five hours difference between America and Europe, while Asia and America's difference is about 12 hours. Thus, data from the Asia-Pacific region is lagged by one day to deal with problems with lack of synchronism in trading hours (Chan, Karolyi, & Stulz, 1992).

5.3 Final sample

After the data selection and pre-processing, our final sample consists of 172 observations from a start sample of 368 observations. The final sample can be seen in table 5.1. Moreover, 68 of the observations originate from America, 67 from Europe, and 37 from Asia-Pacific. All securities have also been listed during the whole estimation period before the event date and have been listed in the GEI over the entire event period. Table 5.2 displays the summary of historical GEI inclusions grouped by region and industry.

Table 5.1: Data selection and cleaning

	Observations	Percent
Full sample	368	100%
Low regional sample size	21	5.7%
Ok regional sample size	347	94.3%
Remaining sample	347	100%
Confounding event	168	48.4%
No confounding event	179	51.6%
Remaining sample	179	100%
No daily trading volume	7	3.9%
Daily trading volume	172	96.1%
Full sample	368	100%
Removed from sample	196	53.3%
Final sample	**172**	**46.7%**

Note: The table reports summary descriptives on how many observations that were removed due to low sample size, confounding events and no daily trading volume.

Table 5.2: Sample by region and industry

	Observations	Percent
Region		
America	68	39.5%
Europe	67	39.0%
Asia-Pacific	37	21.5%
Total	**172**	**100%**
Industry		
	Observations	Percent
Communication services	11	6.4%
Consumer	14	8.1%
Energy	4	2.3%
Financial	70	40.7%
Healthcare	6	3.5%
Industrials	15	8.7%
Information technologies	13	7.6%
Materials	7	4.1%
Real estate	13	7.6%
Utilities	19	11.0%
Total	**172**	**100%**

Note: The table reports summary descriptives on sample size by region and industry.

5.4 Data frequency

Regarding data frequency, we use daily data on stock prices and volume. As we want to test hypotheses related to abnormal returns and trading volume for different daily intervals around the inclusion date, daily data is preferred over weekly data in the event window. For the estimation window, there are pros and cons regarding data frequency at a daily, weekly, or monthly level. The benefit of using daily data is the increased precision in our model because of the increased number of data points. On the other hand, weekly and monthly data offers less precision but is also less affected by outliers (extreme values) since data tends to be more normally distributed at a weekly and monthly level (Brown & Warner, 1985). Simply put, there is a trade-off in precision between increased data points and outliers. However, since our estimation data is winsorized at 5th and 95th percentiles, we avoid the most extreme values since they are replaced with less extreme values, as previously described in section 5.2. Hence, daily data points are used in our estimation window to increase precision.

5.5 Returns and trading volume calculations

As we use the total return index for daily closing prices, returns are calculated as daily changes in the total return index calculated by the following formula:

$$r_{i,t} = \frac{R_{i,t}}{R_{i,t-1}} - 1 \tag{5.2}$$

$r_{i,t}$ is the return of security i at time t, and $R_{i,t}$ is the total return index for security i at time t, while $R_{i,t-1}$ is the total return index for the same security at time $t-1$.

Thereafter, returns are log-transformed to treat skewness in the data and improve the normality of the return distribution (Henderson, 1990):

$$r_{i,t} = \log(r_{i,t}) \tag{5.3}$$

Then, a metric is computed to measure abnormal trading volume. The metric is computed as the number of shares traded for a stock on a particular day, divided by the total amount of outstanding shares. The calculation can be seen from the following figure:

$$V_{i,t} = \frac{VO_{i,t}}{n_{i,t}} \tag{5.4}$$

$V_{i,t}$ is the percentage of traded outstanding shares for security i at time t, $VO_{i,t}$ is the number of shares traded at time t, and $n_{i,t}$ is the total number of shares outstanding. Similar to returns, the literature suggests log transforming the metric to improve the normality of the distribution as the trading volume can be far from normal (Ajinkya & Jain, 1989):

$$V_{i,t} = \log(V_{i,t}) \tag{5.5}$$

6 Event study methodology

This section covers the event study methodology applied to test our hypotheses regarding abnormal returns and trading volume for stocks included in the GEI across regions and industries. Event studies are most commonly applied as a statistical approach to test the efficient market hypothesis. The test is conducted by searching for abnormal stock returns and trading volume induced by the impact of a specific event around a specified time horizon. Commonly referred to as the event window (Kritzman, 1994). As a contribution to historical literature, we will conduct a multi-country event study on a first-of-its-kind Gender Equality Index.

6.1 Event window

When conducting an event study, the first course of action is to define the particular event that the hypotheses are derived from and the event window of interest (MacKinlay, 1997). In our study, the event of interest is a company's inclusion in the GEI. When the particular event of interest has been determined, the next step is to establish the event window's length. The event window is defined as a time frame around index inclusion, with a specified amount of days encompassing the event of interest.

When establishing the length of the event window, there will be a trade-off. A shorter event window might not capture the full effect of the event. In contrast, a longer event window runs the risk of capturing other confounding events, which might impact the abnormalities in returns and trading volume. Therefore, this study applies a 13-day event window to reduce the probability of confounding events occurring during the event window. The event window runs two days before to ten days after the event to differentiate the market's reaction before and after the event date.

Furthermore, to examine which intervals within the event window, the event's effect occurs, event window intervals with varying lengths are applied. Consequently, applying different event window intervals will let us test the efficient market hypothesis and observe if there are any abnormalities in the returns or trading volume surrounding the event.

Thus, this study applies the following event window intervals:

Table 6.1: Event window intervals

Interval	Length
Pre	[-2:-1]
Short	[0:3]
Long	[0:10]
Full	[-2:10]

Note: The table describes the lengths of our event window intervals. Zero denotes the inclusion/event date.

The full-interval [-2:10] aims to capture the effect of the market's reaction to the event over the whole period. If our hypothesis that investors value gender equality holds, positive abnormal returns are expected to be observed in this interval. Oler, Harrison, and Allen (2007) reviewed 62 event studies published in well-known management journals from 1994-2006 and found that 76% of the studies use event windows that close within five days of the event, such as [-1:1] or [-2:2]. Thus, 13 days is a longer event window than the literature applies but will help control for differences in trading hours across regions, and if investors need more time to react to the news.

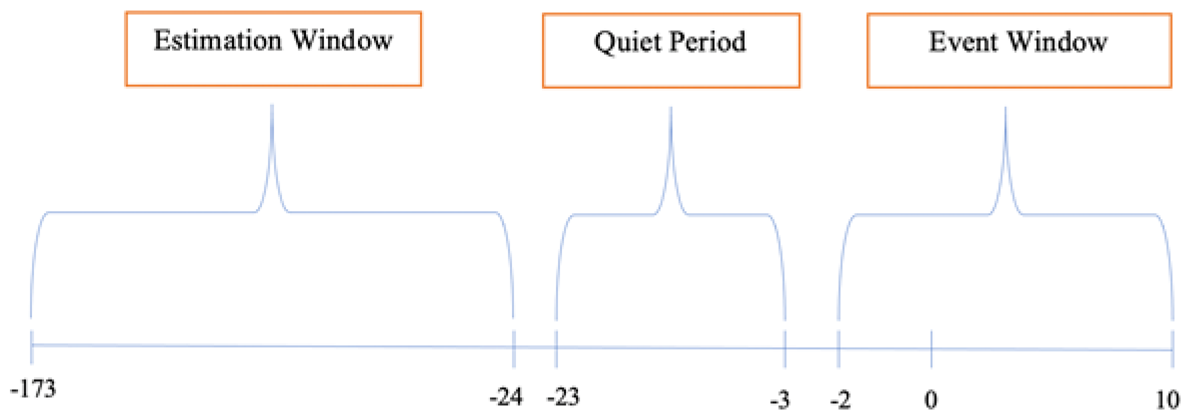
As we believe that markets are efficient in the semi-strong form, four days should be enough time for investors to react to the new information. Thus, we expect to find most abnormalities during the short-interval [0:3]. Moreover, the pre-interval [-2:-1] aims to capture any leakage of insider information about a company's GEI score and potential index inclusion. Finally, the long-interval [0:10] controls whether investors need more than four days to react to the news.

6.2 Estimation window

The next step of the process is to establish the estimation window (MacKinlay, 1997). The estimation window is used as a proxy for normalized returns and volume for a specific company stock and the normalized return of the benchmark indices. These normalized returns are used as parameters to derive abnormal returns in the event window. The time frame of the estimation window is before the event window to ensure that the returns from the event window do not influence the parameters of normalized returns. If the estimation and event window overlap, the normalized return parameters would be biased (MacKinlay, 1997).

Armitage (1995) found that results are not especially sensitive to varying estimation window lengths as long as the length exceeds 100 days. Though in this study, an estimation window of 250 days (150 trading days) is applied. This deviation from the estimation window lengths used in the existing literature is due to the multi-country nature of the event study. N. K. Park (2004) articulates that estimation windows of multi-country event studies are more exposed to country-specific noise. Therefore, the increased length of the estimation period will help reduce this issue as an unusual market movement due to country-specific events tends to be a minor portion of the whole estimation period. Furthermore, if the data used to compute the estimation window parameters is tainted by the event data being included in the estimation window, the abnormal returns would be upward biased. To deal with this concern, a quiet period of 1 month (21 trading days) is included between the estimation window and the event window (Lynch & Mendenhall, 1997).

Figure 6.1: Event study time frame



Note: The figure displays the length of our estimation window, quiet period and event window.

6.3 Normal return model

After establishing the event window, estimation window, and the criteria for stock inclusion, a normal return model must be chosen to capture the event's effect. The normal returns are used as parameters to calculate abnormal returns in the event window. Normal returns are defined as the expected returns of a stock without the event taking place (MacKinlay, 1997). There are two approaches to calculating normal returns: statistical models and economic models. Statistical models rely solely on statistical assumptions about stock returns without relying on economic arguments, while economic models rely on both. Before choosing which normal return model to use, it is beneficial to know each model's advantages and disadvantages. MacKinlay (1997) presents a variety of normal return models such as:

- **Constant Mean Return Model (CMRM):** Assumes that the average return of a stock is the normal return and is constant over time.
- **Market Model (MM):** Assumes a stable linear return between the market return and the return of a stock.
- **Fama-French 3 factor model (FF3):** Aims to explain more of the normal return variation by reducing the variance of abnormal returns.
- **Capital Asset Pricing Model (CAPM):** Equilibrium theory stating that the covariance between a stock and the market portfolio determines normal expected returns (Lintner, 1965; Sharpe, 1964).

The first three models are statistical models, while the last is an economic model. Their advantages and disadvantages can be summarized as follows:

Table 6.2: Advantages and disadvantages with different normal return models

Normal Return Model	Advantges	Disadvantages
CMRM	Simplicity of the model makes it easy to use and often yields results similar to more sophisticated models.	Does not consider market movements. Normal returns could be upward or downwardly biased due to extreme market situations.
MM	Computes precise estimates for stocks that are strongly correlated to an index. Event window considers market movements.	Does not take into account factors that are company related and will not be precise for stocks that are not strongly correlated to an index.
FF3	Takes into account company specific factors and variations such as financial metrics and corporate strategy.	Company specific factors may vary in significance and the model is more complex and time consuming.
CAPM	Simple calculation and easy to use. Assumes that investors hold a diversified portfolio, eliminates unsystematic risk and includes systematic risk.	Output is sensitive to CAPM restrictions and validity of restrictions is questionable (might be unreliable).

Domestic factors such as interest/inflation rates, GDP growth, and exchange rates will influence the data used in a multi-country event study. Therefore, they might significantly impact stock returns, and arguments for applying a multi-factor model, i.e., the FF3, could be made (N. K. Park, 2004). However, there is high correlation between the stocks in the sample and the benchmark indices concerning both mean and median market capitalization. Thus, the multifactor-models' added complexity will not necessarily produce more precise and reliable results than the commonly chosen market model. Consequently, the market model is chosen as the normal return model to calculate abnormal returns.

Beckers, Connor, and Curds (1996) found that changes in equity returns in 19 European countries were affected equally by the influences of global and domestic markets. Additionally, they found that global market factors were more important than country-specific factors within 8 of the studied countries. We argue that these findings are even more valid today as global financial markets have become increasingly intertwined over the past two decades. Therefore, this study will use the market model with regional large-cap indices matched to the sample median market capitalization instead of a multi-factor model to compute the normal return. The formula for the market model is:

$$E(R_{i,t}) = \alpha_i + \beta_i R_{m,t} + \epsilon_{i,t} \tag{6.1}$$

$$E(\epsilon_{i,t}) = 0 \tag{6.2}$$

$R_{i,t}$ and $R_{m,t}$ represent the return for stock i and market portfolio m at time t. ϵ is the error term representing the residual for stock i at time t, with an expected value of 0. b and a is the beta and alpha representing the firm-specific risk and excess return compared to a benchmark market return for stock i. The market return $R_{m,t}$ is calculated using stock indices matched to geographical region and median market capitalization.

The following indices are applied as the benchmarks indices to control for regional differences:

Table 6.3: Indices and median market capitalization

Region	Index	Index	Sample
North America	Russell 1000	\$16.5B	\$10.5B
Europe	MSCI Europe Large Cap	€24.2B	€20.5B
Asia-Pacific	Stoxx 200 Large Cap	\$15.0B	\$22.5B

Note: This table displays median market capitalization of our chosen benchmark indices and samples by region.

Russell 1000 is a subset of the Russell 3000 index. The index comprises the 1000 largest companies in the United States based on market capitalization and is often used as a benchmark for large-cap US companies. Further, the MSCI Europe Large Cap Index is a common benchmark for large-cap European companies, representing 15 developed markets across Europe. Lastly, the Stoxx 200 Large Cap Index includes companies from the Asia-Pacific region. Companies stemming from Japan, Australia, Hong Kong, and Singapore make up the majority of the index weight. The Asia-Pacific sample used in this study is mostly composed of companies from the same countries.

The normal return model chosen for abnormal trading volume is the constant mean return model (CMRM). Brown and Warner (1985) found evidence that this simplified version of the market model often yields similar results as the market model. Therefore, the CMRM is applied to volume estimation. The model assumes that the normal expected trading volume is the average trading volume, which is constant over time. Thus, the formula for the expected trading volume is:

$$E(V_{i,t}) = \hat{V}_{i,t} = \frac{1}{T}\sum_{t=T_1}^{t=T_2} V_{i,t} \tag{6.3}$$

T is the length of the estimation window of 250 days (150 trading days), while T_1 and T_2 are the first and the last day of the estimation window, respectively.

6.4 Abnormal returns and trading volume

After computing the expected normal returns/volume, the next step is to measure abnormal returns and trading volume. Abnormal return/volume is the difference between the observed return/volume in the event window and the calculated expected normal return/volume (MacKinlay, 1997). The formulas for abnormal returns and abnormal trading volume are:

$$AR_{i,t} = R_{i,t} - E(R_{i,t}) \tag{6.4}$$

$$AV_{i,t} = V_{i,t} - E(V_{i,t}) \tag{6.5}$$

Then, daily abnormal return/volume observations are aggregated and averaged by the number N of securities for each day in the event window, yielding daily average abnormal return (AAR) and daily average abnormal volume (AAV). The formulas for AAR and AAV at time t are:

$$AAR_t = \frac{1}{N}\sum_{i=1}^{N} AR_{i,t} \tag{6.6}$$

$$AAV_t = \frac{1}{N}\sum_{i=1}^{N} AV_{i,t} \tag{6.7}$$

Further, (MacKinlay, 1997) states that abnormal returns need to be aggregated across time to determine if the observations are statistically significant. Thus, when daily AAR has been computed, the final step is to accumulate the AARs over the different event window intervals, yielding the cumulated average abnormal return (CAAR). The formula for CAAR is:

$$CAAR = \sum_{t=T_1}^{t=T_2} AAR_t \tag{6.8}$$

T_1 and T_2 denote the first and the last day of the event window interval, respectively.

However, this step is not applied to abnormal trading volume calculations. When examining abnormal trading volume, we want to capture the daily effect over the event window, not specific intervals within the event window.

The final step is to test the significance of the CAARs over the different event window intervals and the daily AAV. To do this, we first need to calculate the AR and AV variance for each stock in the sample. The variance formulas for AR and AV are:

$$\sigma_i^2(AR) = \frac{1}{T}\sum_{t=T_1}^{t=T_2}(AR_{i,t} - \overline{AR}_{i,T})^2 \tag{6.9}$$

$$\sigma_i^2(AV) = \frac{1}{T}\sum_{t=T_1}^{t=T_2}(AV_{i,t} - \overline{AV}_{i,T})^2 \tag{6.10}$$

Where T_1 and T_2 are the first and the last day of the estimation period, respectively. AR/AV is the daily abnormal return/volume for stock i at time t and $\overline{AR}/\overline{AV}$ is the mean abnormal return/volume for stock i over the estimation period T.

After computing the variance of each stock, the sample variance for AAR and AAV are computed:

$$\sigma_{AAR}^2 = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(AR) \tag{6.11}$$

$$\sigma_{AAV}^2 = \frac{1}{N^2}\sum_{i=1}^{N}\sigma_i^2(AV) \tag{6.12}$$

The final step is to test the significance of the CAARs over the different event window intervals and daily AAV. Hence, this study applies a two-tailed t-test to test if CAARs and AAVs are significantly different from zero.

The CAAR and AAV t-statistics are computed as:

$$t(CAAR) = \frac{CAAR}{\sqrt{\sigma_{AAR}^2 \cdot L}} \tag{6.13}$$

$$t(AAV_t) = \frac{AAV_t}{\sqrt{\sigma_{AAV}^2}} \tag{6.14}$$

L represents the length of the event window interval, while σ_{AAR}^2 and σ_{AAV}^2 is the sample variance of AAR and AAV, respectively. A standard normal distribution is assumed.

7 Empirical findings and results

7.1 Abnormal returns

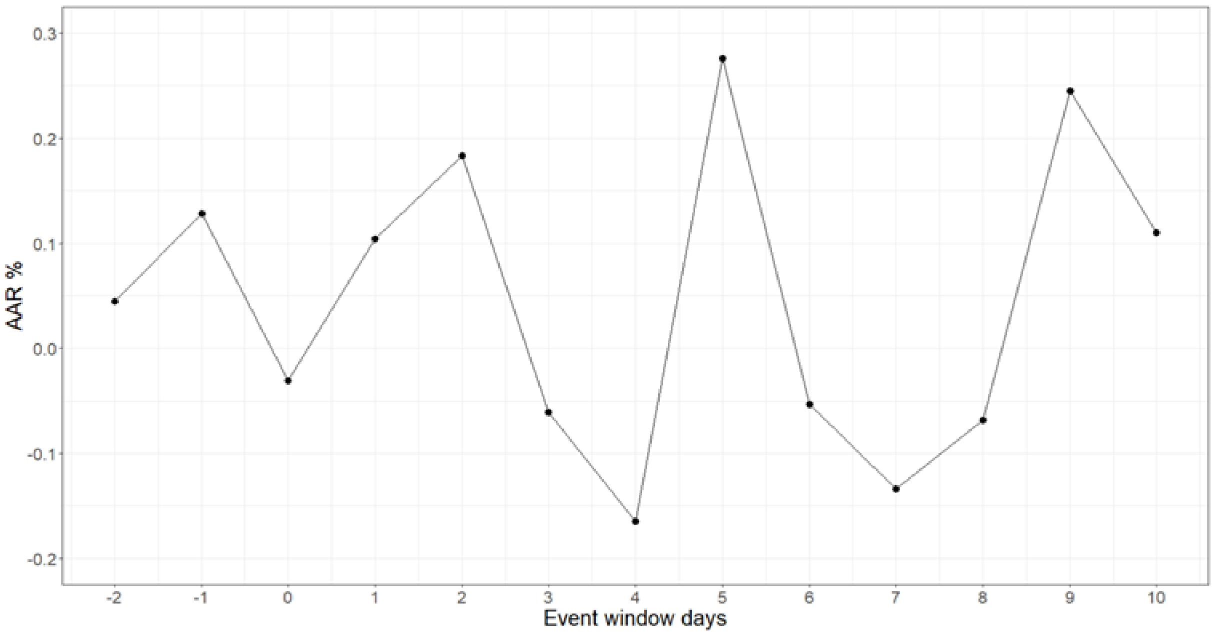
Table 7.1: Daily average abnormal returns over the event window

Event Day	AAR(%)	T-stat
-2	0.045%	0.454
-1	0.128%	1.298
0	-0.031%	-0.315
1	0.104%	1.047
2	0.183%	**1.853***
3	-0.061%	-0.617
4	-0.165%	**-1.672***
5	0.276%	**2.792*****
6	-0.053%	-0.534
7	-0.134%	-1.354
8	-0.068%	-0.683
9	0.245%	**2.483****
10	0.110%	1.116

*Note: This table presents daily average abnormal return (AAR) for the total sample over the event window. Significance: *p<0.10, **p<0.05, ***p<0.01.*

Table 7.1 presents the daily average abnormal return (AAR) for stocks included in the GEI over the period 2016-2020. No significant observation is found at inclusion on day 0. Statically significant AARs, varying in sign and significance, are observed on days 2, 4, 5, and 9.

Figure 7.1: Daily AAR



Note: The figure illustrates daily average abnormal return (AAR) for the total sample over the event window

Figure 7.1 illustrates the daily AAR from 2016-2020 over the full event window interval. AAR is negative on the day of announcement and peaks on days 2, 5, and 9.

Table 7.2: Cumulative average abnormal returns across regions and time periods

		2016-2018		2019		2020		2016-2020	
				All Regions					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.035%	-0.157	0.118%	0.465	0.370%	1.585	0.173%	1.239
Short	[0:3]	0.043%	0.136	0.386%	1.077	0.117%	0.354	0.195%	0.984
Long	[0:10]	-0.678%	-1.295	1.320%	**2.220****	0.287%	0.524	0.407%	1.241
Full	[-2:10]	-0.713%	-1.253	1.438%	**2.224****	0.657%	1.104	0.580%	1.627
				AM					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	0.368%	1.249	0.235%	0.654	0.865%	**1.793***	0.470%	**2.118****
Short	[0:3]	-0.229%	-0.551	-0.324%	-0.636	-0.742%	-1.088	-0.424%	-1.349
Long	[0:10]	-0.398%	-0.577	2.639%	**3.129*****	-0.211%	-0.187	0.821%	1.575
Full	[-2:10]	-0.031%	-0.041	2.874%	**3.135*****	0.653%	0.531	1.291%	**2.280****
				EU					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.482%	-0.922	-0.236%	-0.473	0.621%	**2.199****	0.155%	0.667
Short	[0:3]	-0.176%	-0.239	1.223%	**1.732***	0.682%	**1.708***	0.698%	**2.128****
Long	[0:10]	-0.629%	-0.513	-0.270%	-0.231	0.557%	0.841	0.085%	0.157
Full	[-2:10]	-1.110%	-0.834	-0.506%	-0.398	1.177%	1.636	0.240%	0.406
				A/P					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.294%	-0.728	0.411%	0.875	-1.521%	**-2.554****	-0.340%	-1.207
Short	[0:3]	0.739%	1.295	0.444%	0.669	0.001%	0.001	0.420%	1.054
Long	[0:10]	-1.217%	-1.286	1.259%	1.145	0.417%	0.298	0.228%	0.346
Full	[-2:10]	-1.511%	-1.459	1.670%	1.400	-1.104%	-0.727	-0.111%	-0.155

*Note: This table presents cumulative average abnormal return (CAAR) over different time periods and regions. Significance: *p<0.10, **p<0.05, ***p<0.01.*

Table 7.2 presents the cumulative average abnormal return (CAAR) for stocks included in the GEI over the periods 2016-2018, 2019, 2020, and 2016-2020. Due to low sample size in 2016, 2017, and 2018, the samples are combined.

Over the full time horizon from 2016-2020, the all-regions sample yields no significant observations around inclusion in the GEI. Thus, hypothesis 1 is rejected. Further, no significant observations are found in the Asia-Pacific (A/P) sample, but the North-American (AM) and European (EU) samples have statistically significant positive returns at a 5% level over different event window intervals. The results indicate that the AM and EU regions react positively to the news of inclusion in the GEI, while the A/P region reacts neutrally. As regional differences are observed with varying signs and significance, hypothesis 4 is accepted.

Similar results are observed in 2019 and 2020, where the AM and EU samples have statistically significant positive abnormal returns varying in significance over different event window intervals. In 2019, the all-regions sample yielded positive abnormal returns of 1,44% at the 5% level over the full-interval. We also observe a shift in the all-regions sample's returns from negative but not statistically significant during 2016-2018 to positive and statistically significant in 2019. In 2020 the abnormal returns are positive but not statistically significant.

In 2020 there are signs of leakage as all respective regions have statistically significant returns the days before the announcement in the pre-interval. The AM and EU samples have positive abnormal returns of 0,86% and 0,62% at 10% and 5% levels. In contrast, the A/P sample has negative abnormal returns of -1,52% at the 5% level. The observations indicate that the A/P region interprets inclusion in the GEI as negative news. Hypothesis 3 is rejected as 2020 is the only year we observe signs of leakage, and no significant observation is found in the pre-interval for the all-regions sample.

Table 7.3: Cumulative average abnormal returns across industries

		Communication Services		**Consumer**	
Interval	Length	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.452%	-0.877	0.276%	0.471
Short	[0:3]	-0.618%	-0.849	-1.003%	-1.213
Long	[0:10]	-1.369%	-1.134	-0.068%	-0.050
Full	[-2:10]	-1.820%	-1.387	0.207%	0.139
		Energy		**Financial**	
Interval	Length	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.128%	-0.106	-0.146%	-0.766
Short	[0:3]	-1.905%	-1.112	0.448%	1.661
Long	[0:10]	-8.201%	**-2.887***	0.673%	1.504
Full	[-2:10]	-8.329%	**-2.697***	0.527%	1.083
		Healthcare		**Industrials**	
Interval	Length	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	0.400%	0.363	0.292%	0.717
Short	[0:3]	0.637%	0.408	-0.771%	-1.338
Long	[0:10]	4.133%	1.597	-1.299%	-1.360
Full	[-2:10]	4.533%	1.611	-1.007%	-0.970
		Materials		**Information Technology**	
Interval	Length	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.248%	-0.214	1.060%	1.770
Short	[0:3]	1.672%	1.019	-0.496%	-0.586
Long	[0:10]	1.859%	0.681	0.991%	0.706
Full	[-2:10]	1.611%	0.545	2.051%	1.343
		Real Estate		**Utilities**	
Interval	Length	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	0.399%	0.936	0.911%	**3.022*** **
Short	[0:3]	0.882%	1.465	1.463%	**3.434*** **
Long	[0:10]	0.195%	0.195	2.235%	**3.163*** **
Full	[-2:10]	0.593%	0.547	3.146%	**4.095*** **

*Note: This table presents cumulative average abnormal return (CAAR) across industries. Significance: *p<0.10, **p<0.05, ***p<0.01.*

Further, when grouping the sample by industry sectors, one out of ten sectors represented yield significant results around inclusion. The results indicate that the Utilities sector views gender equality and inclusion in the GEI as value increasing. Positive abnormal returns are seen at the 1% level in all event window intervals. Additionally, we find that the Energy sector negatively views GEI inclusion, with negative abnormal returns at the 10% level over the full-interval and long-interval. Still, no significant results are observed around the inclusion in the short-interval for the Energy sector. Nevertheless, because of the low sample size within each industry, the results might be biased. Therefore, these findings might not be sufficient to draw definite conclusions regarding whole industries. Hence, hypothesis 5 is rejected.

7.2 Abnormal volume

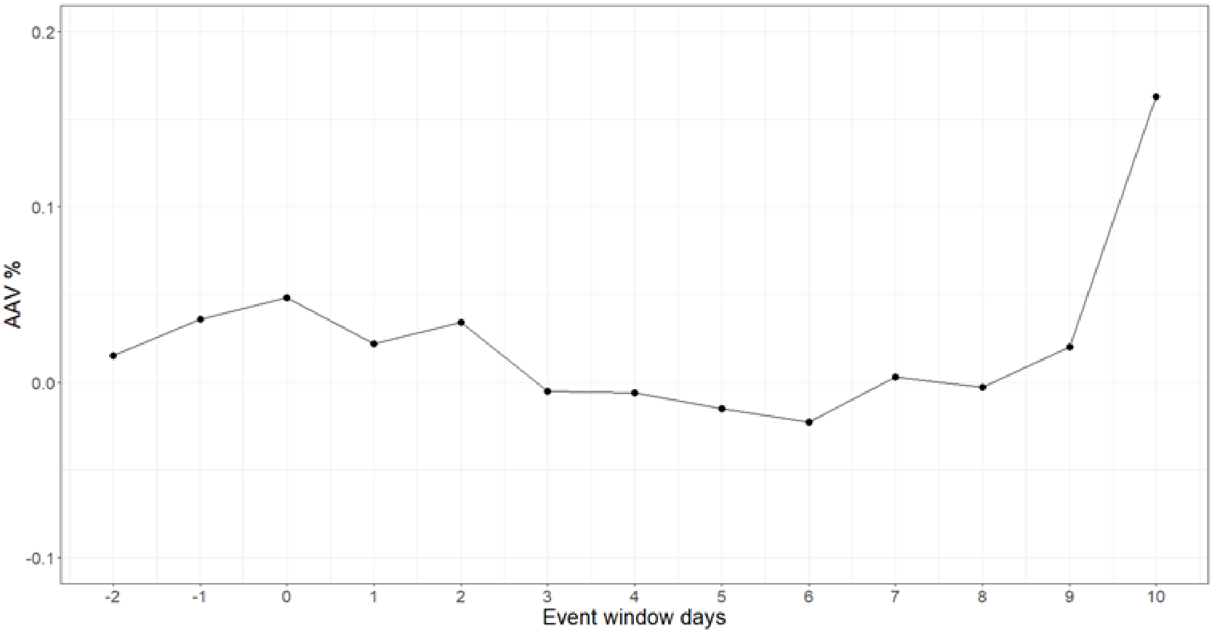
Table 7.4: Daily average abnormal trading volume over the estimation window

Event Day	**AAV(%)**	**T-stat**
-2	0.015%	0.523
-1	0.036%	1.272
0	0.048%	**1.719***
1	0.022%	0.790
2	0.034%	1.233
3	-0.005%	-0.182
4	-0.006%	-0.207
5	-0.015%	-0.528
6	-0.023%	-0.821
7	0.003%	0.101
8	-0.003%	-0.097
9	0.020%	0.709
10	0.163%	**5.834*****

*Note: This table presents daily average abnormal trading volume (AAV) for the total sample over the event window. Significance: *p<0.10, **p<0.05, ***p<0.01.*

Table 7.4 presents the daily average abnormal trading volume (AAV) for stocks included in the GEI over the period 2016-2020. On the day of inclusion, there is a very low but significantly positive AAV of 0,048% at the 10% level. Furthermore, we observe a statistically significant AAV of 0,16% at the 1% level on the event window's last day. This spike in AAV might be caused by anticipation or leakage of a new event coming up the days after the event window used in this study. Nevertheless, because of the lack of additional significant observations around the inclusion, hypothesis 2 is rejected.

Figure 7.2: Daily AAV



Note: The figure illustrates daily average abnormal trading volume (AAV) for the total sample over the event window.

Figure 7.2 illustrates the daily AAV from 2016-2020 over the full event window interval. AAV increases the two days prior to the announcement before it peaks on the day of the announcement and becomes statistically significant. After the announcement, AAV is not statistically significant before it peaks again on the event window's last day.

7.3 Interpretation of results

Overall, the results of this study yield few significant observations, possibly due to the existing expectation of high CSR standards. The three first hypotheses formulated in this study are based on information from the literature review in section 3. Our hypotheses rely on the following assumptions:

- Markets are efficient.
- Asymmetric information is present.
- Inclusion in the GEI acts as a signal to investors.
- There is an index effect associated with inclusion in the GEI.

This study assumes that markets are efficient in the semi-strong form. Thus, according to the efficient market hypothesis, the news should be incorporated into the price after a few days. Consequently, GEI inclusion has to be viewed as new information by the market. Before the announcement, Bloomberg is the exclusive holder of this information. Therefore, it should not already be incorporated into the stock price. A more viable explanation for the lack of significant observations might be that the market has already incorporated CSR expectations in the companies' stock prices.

Furthermore, one of the criteria for GEI inclusion is that companies must have a market capitalization of over 1B USD. As these are all large-cap companies with a lot of attention, it would make sense that a certain level of expectations to a company's CSR practices is already reflected in the stock price. Thus, while inclusion in the GEI might be new information to the market, there is a lack of market reaction as these companies are already expected to have high CRS standards. Consequently, inclusion in the GEI is seen as a further contribution to already high CSR standards.

The hypotheses further rely on the assumptions that there are asymmetries in the information available between companies and their investors. The signal inclusion in the GEI sends to the market should decrease these asymmetries. Therefore, the GEI acts as a neutral third-party mediator between companies and investors by vouching for and signaling which companies excel at gender equality transparency in the workplace. Most ESG indices score companies on an overall assessment of the three fields of ESG. On the other hand, the GEI differentiates itself from other ESG indices by narrowing the CSR requirements for inclusion to gender equality transparency.

In reaction to the increased global focus on ESG and CSR, most companies willingly publish their commitment to CSR. According to a report from the Governance and Accountability Institute (2019), 86% of the companies in the S&P500 issued sustainability reports compared to roughly 20% in 2011. This increase in sustainability reporting is not surprising as high CSR standards are proven to increase firm value by reducing risk. While inclusion in the GEI might be viewed as a positive signal that reduces information asymmetry within the gender equality dimension of CSR, the signal might not be viewed as valuable. Hence, the reduction in asymmetries does not affect the overall price-incorporated expectation of CSR enough for markets to react. Hawn et al. (2018) found similar results when they study the US market and found that investors are becoming more neutral to CSR news and index inclusions

The last assumption our three first hypotheses rely on is that an index effect is associated with inclusion in the GEI. The price pressure hypothesis articulates that stocks included in an index experience a rapid increase in demand around the inclusion. Thus increasing trading volume and causing prices to diverge from its information-efficient values. The hypothesis assumes that index inclusion holds no new information in itself. The price increase is due to shareholders being compensated for the transaction costs and portfolio risk they bear when they provide liquidity by selling stocks due to the increased demand.

Furthermore, the price pressure hypothesis relies on the assumption that a considerable number of investors track the index and rebalance their portfolio accordingly. Even though GEI companies are all large-cap companies followed by a large number of investors, there is no ETF to date that tracks the GEI. The lack of an ETF tracking the index might explain the lack of significant observations for abnormal returns and trading volume. Consequently, an ETF tracking the index would be responsible for a large amount of the increase in demand and trading volume depending on the ETF's size and potential investors tracking the ETF.

According to the information signaling, awareness, and liquidity hypotheses, inclusion should cause a price increase as companies included in the GEI gain more attention than their peers combined with the positive signal inclusion sends to the market. The signal from inclusion reduces information asymmetry. Consequently, bid-ask spreads, shadow, and information costs decreases as liquidity increases, thus increasing value. However, the increased awareness might not affect the stock price as investors have different views of whether CSR is value-adding or value-destroying.

Furthermore, Cheung and Roca (2013) examined this and introduced the corporate sustainability taste and sustainability redundancy hypothesis. The two theories suggest that investors either see corporate sustainability as financial strength or a burden. The corporate sustainability taste theory suggests that investors with a taste for sustainable firms perceive additional utility from holding these stocks on top of the returns each stock delivers. Further, this aligns with the imperfect substitutes hypothesis, which assumes that investors perceive each security as a unique asset without perfect substitutes. Therefore, investors will select stocks based on their characteristics and individual preference, and the price depends on supply and demand. Thus, stocks included in the GEI should experience an increase in price due to the demand from this group of investors.

On the other hand, the sustainability redundancy theory suggests that investors see CSR as a financial constraint. Hence, investors cannot create optimal portfolios based on risk minimization and return maximization. Therefore, stocks included in the GEI should experience negative returns. Consequently, these different investors offset each other's effect as their view of CSR is already determined, which would explain the lack of significant observations.

The downward sloping demand curve hypothesis articulates that if there is a downward sloping demand curve due to imperfect substitutes, stock prices will be sensitive to demand shocks. Therefore, if the demand for a stock suddenly increases, the price should also increase until it reaches a new equilibrium. Inclusion in the GEI should be accompanied by increased demand from investors who actively seek gender-diverse companies. GEI inclusions do not experience this as there is almost no increase in volume over the event window.

Overall, the results indicate that gender equality is most highly valued in the EU and AM regions and least valued in the A/P region. The EU and AM regions experience an increase in share price around the inclusion in 2019, 2020, and over the whole period from 2016-2020. There is only one significant observation from the A/P region, where we observe negative abnormal returns the days before the announcement in 2020. These findings align with the findings from Consolandi et al. (2009), Lackmann et al. (2012) and Cheung and Roca (2013). They argue that CSR is most commonly valued in the US and EU regions, whereas the Asia-Pacific region views CSR as a financial constraint.

The findings of this study align with the overall intuitive perception of gender equality on a global level. According to World Economic Forum (2020) gender equality is furthest along in Europe and North America. Thus, it makes sense that the EU and AM region is where inclusion in a gender equality index is valued most. Asia is the region that has the furthest way to go regarding gender equality. Even though there are high levels of gender equality in the Pacific region, the Asia-Pacific sample used in this study is composed primarily of Asian companies.

7.4 Control

Furthermore, a cross-sectional analysis is conducted to ensure that the results obtained are not biased by firm-specific traits, region of origin, or industry. The total sample size is reduced by 11 observations due to missing data. See table A1.1 and figures A1.4 and A1.5 in the appendix for descriptive data and boxplots of variables used in the cross-sectional analysis before and after pre-processing. Cumulative abnormal returns (CAR) for each company over the short interval [0:3] are regressed on a range of variables to capture the sensitivity of each company's CAR, relative to common valuation metrics. Regional and industrial dummies are also included as a further control for hypotheses 4 and 5 regarding differences in regions and industries with the AM region as the baseline region. Thus, each company's CAR is regressed on the following firm-specific traits:

- **SIZE:** Log transformed market capitalization is used as a proxy for company size. Fama and French (1992) developed the three-factor asset pricing model and found that market capitalization significantly influences stock returns. Additionally, they found that small companies tend to outperform larger companies.
- **VALUE:** Price to Book (P/B) ratios are commonly used to compare companies on their relative value compared to their book value. Companies with high P/B ratios are defined as growth stocks, and companies with low P/B ratios are defined as value stocks. Historical literature has repeatedly found that value stocks outperform growth stocks in the long run.
- **LEVERAGE:** Debt over shareholder equity (D/E) is a financial leverage ratio. Higher leverage indicates higher levels of financial risk because of the large proportion of debt. Debt to Equity is chosen as the financial leverage ratio over Debt to Assets (D/A) due to the size of the companies in the sample. D/E will let us get a more insightful look at the companies' leveraged position compared to the D/A ratio, which includes intangible assets such as Goodwill from merger activities.
- **PROFITABILITY:** Return on Assets (ROA) is a profitability ratio that measures how efficiently a company uses its assets to generate earnings. A higher percentage of ROA indicates higher asset efficiency.

Table 7.5: Cross-sectional study on cumulative abnormal return

	Dependent variable:		
	CAR		
	(1)	(2)	(3)
Log(Mcap)	0.002	0.002	0.001
	(0.002)	(0.002)	(0.002)
P/B	−0.0001	−0.0001	−0.00001
	(0.0003)	(0.0003)	(0.0003)
D/E	−0.00000	−0.00000	−0.00001
	(0.00001)	(0.00001)	(0.00001)
ROA	−0.0002	−0.00001	0.0001
	(0.0004)	(0.0004)	(0.0004)
Europe		0.011**	
		(0.005)	
Asia		0.007	
		(0.005)	
Consumer			−0.002
			(0.011)
Energy			−0.013
			(0.015)
Financial			0.012
			(0.009)
Healthcare			0.013
			(0.013)
Industrials			−0.001
			(0.010)
‘Information tech‘			0.00003
			(0.011)
Materials			0.031**
			(0.013)
‘Real estate‘			0.014
			(0.011)
Utilities			0.021**
			(0.010)
Constant	−0.042	−0.041	−0.039
	(0.038)	(0.038)	(0.039)
Observations	161	161	161
R^2	0.011	0.045	0.128
Adjusted R^2	−0.015	0.008	0.050
Residual Std. Error	0.026 (df = 156)	0.026 (df = 154)	0.025 (df = 147)
F Statistic	0.421 (df = 4; 156)	1.219 (df = 6; 154)	1.653* (df = 13; 147)

*Note: This table shows the result of CARs over the short event window interval [0:3] regressed on firm-specific traits, regional and industry dummies. Significance: *p<0.10, **p<0.05, ***p<0.01.*

The results of the cross-sectional analysis indicate that firm-specific traits do not affect CARs. When introducing regional dummies, we observe that the Europe dummy positively affects CARs, aligning with our findings. Further, we observe that the Materials and Utilities industry dummies positively affect CARs. However, these results might be biased by a low sample size or industry-specific events that our data does not capture. Furthermore, because of the low R-squared, our analysis has low explanatory power. Thus, the multi-factor analysis and its variables offer little explanation regarding the sign of the CARs observed in the days following inclusion in the GEI. Finally the regressions are tested for heteroscedasticity by plotting residuals against fitted values, see figure A1.1, A1.2, and A1.3 in the appendix.

7.5 Robustness check

Two robustness checks were performed to ensure that our CAAR results were not biased by methodology choice. Hence, we compared our results when using 150 trading days against the results using 200 and 100 trading days in the estimation window. The results obtained were similar, with minor differences in signs and significant observations. Results from the robustness checks are located in tables A1.2 and A1.3 in the appendix.

8 Conclusion

This thesis aimed to investigate whether global markets reward firms that show a commitment to gender equality in the workplace. Ultimately, inclusion on Bloomberg's Gender Equality Index (GEI) was used as a proxy for transparency within gender equality reporting. We conducted a short-run event study, analyzing stocks included in the GEI from 2016-2020. Thus, we measured the effect inclusion had on share price and trading volume for new constituents, by investigating abnormal returns and abnormal trading volume around the annual announcement date.

We do not observe any significant positive price effect from inclusion for the entire sample covering all the regions around the announcement day. Therefore, we reject our main hypothesis stating that GEI inclusion will yield abnormal returns. However, we observe significant positive abnormal returns in the European and North American regions the days following and the days before the announcement, respectively. In contrast, no significant observations are found in the Asia-Pacific region. Hence, we accept hypothesis 4, stating that the effects of inclusion differ between geographical regions.

Furthermore, we observe a shift in the sign and significance of the abnormal returns over the full event window interval, from being negative but not significant in 2016-2018, to positive and significant in 2019. In 2020 the abnormal returns stay positive but lose significance. The results indicate an increasingly positive view of gender equality in the workplace over the years. In 2020 the respective regions show significant positive (negative) abnormal returns during the pre-event window interval, indicating signs of leakage. As this is only observed in 2020, we reject hypothesis 3, stating that there is information leakage prior to the inclusion date.

Moreover, we also reject hypothesis 5 stating that the effects of inclusion differ between industries, seeing how the utilities industry is the only industry where we find abnormal returns around the announcement. Consequently, each industry's low sample size makes it hard to draw reliable conclusions. Further, hypothesis 2 stating that GEI inclusion yields abnormal trading volume is also rejected. The only significant trading volume observation around the announcement is on the announement date, but the result is barely significant at the 10% level.

Concluding, this study fails to find any convincing evidence that investors value gender equality in the workplace on a global scale. However, it seems that the North American and European regions are positive to a firm's commitment to gender equality, while the Asia-Pacific region is neutral.

9 Limitations

The empirical analysis conducted in this thesis is exposed to different factors that might reduce the results' validity. Most notably, the methodology applied to calculate abnormal returns, what normal return model to use, and the limited sample size available. The results obtained will be influenced by variations in these factors, especially in multi-country event studies.

Stock returns in multi-country event studies are influenced by domestic factors such as interest/inflation rates, GDP growth, and exchange rates. Thus, a multi-factor model might produce more reliable results than the single-factor market model used in this study. Although, according to Beckers et al. (1996), global market factors influence equity returns more than country-specific factors.

This study uses regional indices as benchmarks for the market return in the respective geographical regions. Therefore, our results are potentially exposed to country-specific biases as domestic events might not be captured by the regional indices, which could influence the abnormal returns observed.

Furthermore, as the GEI was founded in 2016, the time horizon and the number of inclusions to the index are limited. The empirical results might, therefore, be affected by the limited sample size. Additionally, the results might be biased by the lack of synchronism in trading hours between geographical regions. As such, markets cannot react simultaneously to the announcement, which complicates the effort to measure the index effect.

10 Suggestion for further studies

Gender inequality is a pressing matter that, in all likelihood, will continue to receive increased attention. Even though the GEI is a relatively new index, the number of constituents has increased every year. As the index expanded to cover all industries from 2018, it is only reasonable to assume that the index will attract more attention in the years to come. Therefore, we suggest that a similar event study is performed in a few years with new additional data to validate the findings of this thesis.

Further, it would be interesting to examine the index effect for deletions from the GEI while controlling for company-specific events. Because of the low sample size of exclusions without confounding events, this study does not measure the effect exclusion from the GEI has on abnormal returns and trading volume. Thus, examining these deletions while controlling for company-specific events would generate a more thorough analysis of the index effect.

Lastly, we suggest that a similar event study is done on the GEI using domestic indices as benchmarks for market returns and a multi-factor model to calculate abnormal returns. It would also be interesting to conduct a study using the same methodology on a similar index such as the MSCI Europe Women's Leadership Index or a domestic study on the Norwegian SHE Index to ensure that this study's empirical results are valid.

References

Ajinkya, B. B., & Jain, P. C. (1989). The behavior of daily stock market trading volume. *Journal of accounting and economics*, *11*(4), 331–359. doi: https://doi.org/10.1016/0165-4101(89)90018-9

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500. doi: https://doi.org/10.2307/1879431

Amihud, Y., & Mendelson, H. (1986). Asset pricing and the bid-ask spread. *Journal of financial Economics*, *17*(2), 223–249. doi: https://doi.org/10.1016/0304-405X(86)90065-6

Arayssi, M., Dah, M., & Jizi, M. (2016). Women on boards, sustainability reporting and firm performance. *Sustainability Accounting, Management and Policy Journal*. doi: https://doi.org/10.1108/SAMPJ-07-2015-0055

Armitage, S. (1995). Event study methods and evidence on their performance. *Journal of economic surveys*, *9*(1), 25–52. doi: https://doi.org/10.1111/j.1467-6419.1995.tb00109.x

Barry, C. B., & Brown, S. J. (1985). Differential information and security market equilibrium. *Journal of financial and quantitative analysis*, 407–422. doi: https://doi.org/10.2307/2330758

Bebczuk, R. N. (2003). *Asymmetric information in financial markets: introduction and applications.* Cambridge University Press.

Beckers, S., Connor, G., & Curds, R. (1996). National versus global influences on equity returns. *Financial Analysts Journal*, *52*(2), 31–39. doi: https://doi.org/10.2469/faj.v52.n2.1978

Beneish, M. D., & Gardner, J. C. (1995). Information costs and liquidity effects from changes in the dow jones industrial average list. *Journal of Financial and Quantitative Analysis*, 135–157. doi: https://doi.org/10.2307/2331257

Bloomberg. (2016). *Bloomberg launches financial services gender-equality index.* Retrieved from `https://www.bloomberg.com/company/press/bloomberg-launches-financial-services-gender-equality-index/`

Bloomberg. (2020a). *2020 bloomberg gender-equality index: Data fact sheet.* Retrieved from `https://data.bloomberglp.com/company/sites/46/2020/01/EXEC_2020_GEI_SFCT.pdf`

Bloomberg. (2020b). *Become a gei member company.* Retrieved from `https://www.bloomberg.com/gei/become-a-gei-member-company/`

Bloomberg. (2020c). *Gender-equality index: Invest in a more equal future.* Retrieved from `https://data.bloomberglp.com/company/sites/46/2020/01/2020GEI_BCH_WEB1.pdf`

Bloomberg. (2020d). *Gender-equality index methodology.* Retrieved from `https://data.bloomberglp.com/company/sites/46/2020/06/GEI-2021-Methodology.pdf`

Bloomberg. (2020e). *Letter from our founder.* Retrieved from `https://www.bloomberg.com/gei/letter-from-founder/`

Boyd, J. H., & Prescott, E. C. (1986). Financial intermediary-coalitions. *Journal of Economic theory*, *38*(2), 211–232. doi: https://doi.org/10.1016/0022-0531(86)90115-8

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of financial economics*, *14*(1), 3–31. Retrieved from `https://doi.org/`

10.2307/3003485

Chan, K. C., Karolyi, G. A., & Stulz, R. (1992). Global financial markets and the risk premium on us equity. *Journal of Financial Economics*, *32*(2), 137–167. doi: https://doi.org/10.1016/0304-405X(92)90016-Q

Cheung, A. (2011). Do stock investors value corporate sustainability? evidence from an event study. *Journal of Business Ethics*, *99*(2), 145–165. doi: https://doi.org/10.1007/s10551-010-0646-3

Cheung, A., & Roca, E. (2013). The effect on price, liquidity and risk when stocks are added to and deleted from a sustainability index: Evidence from the asia pacific context. *Journal of Asian Economics*, *24*, 51–65. doi: https://doi.org/10.1016/j.asieco.2012.08.002

Connelly, B. L., Certo, S. T., Ireland, R. D., & Reutzel, C. R. (2011). Signaling theory: A review and assessment. *Journal of management*, *37*(1), 39–67. doi: https://doi.org/10.1177/0149206310388419

Consolandi, C., Jaiswal-Dale, A., Poggiani, E., & Vercelli, A. (2009). Global standards and ethical stock indexes: The case of the dow jones sustainability stoxx index. *Journal of Business Ethics*, *87*(1), 185–197. doi: https://doi.org/10.1007/s10551-008-9793-1

Datastream. (2020). *Total return index.* Thomson Reuters. Retrieved from https://www.bloomberg.com/gei/letter-from-founder/

De Lucia, C., Pazienza, P., & Bartlett, M. (2020). Does good esg lead to better financial performances by firms? machine learning and logistic regression models of public enterprises in europe. *Sustainability*, *12*(13), 5317. doi: https://doi.org/10.3390/su12135317

Dixon, S., Dolan, K., Hunt, V., & Prince, S. (2020). Diversity wins, how inclusion matters. *McKinsey & Co., May.* Retrieved from https://www.mckinsey.com/featured-insights/diversity-and-inclusion/diversity-wins-how-inclusion-matters

Doane, D., & Abasta-Vilaplana, N. (2005). *The myth of csr* (Vol. 3) (No. 3). Stanford social innovation review. Retrieved from https://www.researchgate.net/profile/Deborah_Doane/publication/235356500_The_myth_of_CSR/links/5440f98e0cf2a76a3cc5c0eb/The-myth-of-CSR.pdf

Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383–417. doi: https://doi.org/10.2307/2325486

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. *the Journal of Finance*, *47*(2), 427–465. doi: https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Forum, W. E. (2020). *The global gender gap index 2020 rankings.* Retrieved from https://reports.weforum.org/global-gender-gap-report-2020/the-global-gender-gap-index-2020-rankings/

Friede, G., Busch, T., & Bassen, A. (2015). Esg and financial performance: aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, *5*(4), 210–233. doi: https://doi.org/10.1080/20430795.2015.1118917

Fulton, M., Kahn, B., & Sharples, C. (2012). Sustainable investing: Establishing long-term value and performance. *Available at SSRN 2222740*. doi: http://dx.doi.org/10.2139/ssrn.2222740

Giese, G., Lee, L.-E., Melas, D., Nagy, Z., & Nishikawa, L. (2019). Foundations of esg investing: how esg affects equity valuation, risk, and performance. *The Journal of Portfolio Management*, *45*(5), 69–83. doi: https://doi.org/10.3905/

jpm.2019.45.5.069

Gladysek, O., & Chipeta, C. (2012). The impact of socially responsible investment index constituent announcements on firm price: Evidence from the jse. *South African Journal of Economic and Management Sciences*, *15*(4), 429–439. Retrieved from `http://www.scielo.org.za/scielo.php?script=sci_arttext&pid=S2222-34362012000400007&lng=en&tlng=en`

Goetzmann, W. N., & Garry, M. (1986). Does delisting from the s&p 500 affect stock price? *Financial Analysts Journal*, *42*(2), 64–69. doi: https://doi.org/10.2469/faj.v42.n2.64

Harris, L., & Gurel, E. (1986). Price and volume effects associated with changes in the s&p 500 list: New evidence for the existence of price pressures. *the Journal of Finance*, *41*(4), 815–829. doi: https://doi.org/10.1111/j.1540-6261.1986.tb04550.x

Hawn, O., Chatterji, A. K., & Mitchell, W. (2018). Do investors actually value sustainability? new evidence from investor reactions to the dow jones sustainability index (djsi). *Strategic Management Journal*, *39*(4), 949–976. doi: https://doi.org/10.1002/smj.2752

Henderson, G. V. (1990). Problems and solutions in conducting event studies. *Journal of Risk and Insurance*, 282–306. doi: https://doi.org/10.2307/253304

Hess, A. C., & Frost, P. A. (1982). Tests for price effects of new issues of seasoned securities. *The Journal of Finance*, *37*(1), 11–25. doi: https://doi.org/10.1111/j.1540-6261.1982.tb01092.x

Institute, G. A. (2019). *Navigating the way to sustainability.* Retrieved from `https://www.ga-institute.com/press-releases/article/flash-report-86-of-sp-500-indexR-companies-publish-sustainability-responsibility-reports-in-20.html`

Jain, P. C. (1987). The effect on stock price of inclusion in or exclusion from the s&p 500. *Financial Analysts Journal*, *43*(1), 58–65. doi: https://doi.org/10.2469/faj.v43.n1.58

Jiraporn, P., Jiraporn, N., Boeprasert, A., & Chang, K. (2014). Does corporate social responsibility (csr) improve credit ratings? evidence from geographic identification. *Financial Management*, *43*(3), 505–531. doi: https://doi.org/10.1111/fima.12044

Joshi, S., Pandey, V., & Ros, R. B. (2017). Asymmetry in stock market reactions to changes in membership of the dow jones sustainability index. *The Journal of Business Inquiry*, *16*(1 Spec), 12–35. Retrieved from `http://161.28.100.113/index.php/jbi/article/view/74`

Kappou, K., & Oikonomou, I. (2016). Is there a gold social seal? the financial effects of additions to and deletions from social stock indices. *Journal of Business Ethics*, *133*(3), 533–552. doi: http://dx.doi.org/10.1007/s10551Âň014Âň2409Âňz

Kraus, A., & Stoll, H. R. (1972). Price impacts of block trading on the new york stock exchange. *The Journal of Finance*, *27*(3), 569–588. doi: https://doi.org/10.1111/j.1540-6261.1972.tb00985.x

Kritzman, M. P. (1994). What practitioners need to know... about event studies. *Financial Analysts Journal*, *50*(6), 17–20. doi: https://doi.org/10.2469/faj.v50.n6.17

Lackmann, J., Ernstberger, J., & Stich, M. (2012). Market reactions to increased reliability of sustainability information. *Journal of business ethics*, *107*(2), 111–128. doi: https://doi.org/10.1007/s10551-011-1026-3

Lintner, J. (1965). Security prices, risk, and maximal gains from diversification. *The journal of finance*, *20*(4), 587–615. doi: https://doi.org/10.2307/2977249

Lynch, A. W., & Mendenhall, R. R. (1997). New evidence on stock price effects associated with changes in the s&p 500 index. *The Journal of Business*, *70*(3), 351–383. doi: https://doi.org/10.1086/209722

MacKinlay, A. C. (1997). Event studies in economics and finance. *Journal of economic literature*, *35*(1), 13–39. Retrieved from `http://www.jstor.org/stable/2729691`

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *Journal of economic perspectives*, *17*(1), 59–82. doi: 10.1257/089533003321164958

McGuire, J. B., Sundgren, A., & Schneeweis, T. (1988). Corporate social responsibility and firm financial performance. *Academy of management Journal*, *31*(4), 854–872. doi: https://doi.org/10.5465/256342

McKinsey. (2015). *The power of parity: How advancing women's equality can add $12 trillion to global growth.* McKinsey & Company London. Retrieved from `https://www.mckinsey.com/featured-insights/employment-and-growth/how-advancing-womens-equality-can-add-12-trillion-to-global-growth`

Merton, R. C. (1987). A simple model of capital market equilibrium with incomplete information. *The Journal of Finance*, *42*(3), 483-510. doi: https://doi.org/10.1111/j.1540-6261.1987.tb04565.x

Mikkelson, W. H. (1981). Convertible calls and security returns. *Journal of Financial Economics*, *9*(3), 237–264. doi: https://doi.org/10.1016/0304-405X(81)90027-1

Mills, T. C., Coutts, J. A., & Roberts, J. (1996). Misspecification testing and robust estimation of the market model and their implications for event studies. *Applied Economics*, *28*(5), 559–566. doi: https://doi.org/10.1080/000368496000000035

Nakai, M., Yamaguchi, K., & Takeuchi, K. (2013). Sustainability membership and stock price: an empirical study using the morningstar-sri index. *Applied Financial Economics*, *23*(1), 71–77. doi: https://doi.org/10.1080/09603107.2012.709602

Nordea. (2017). *Nordic ideas: Strategy & quant.* Retrieved from `https://nordeamarkets.com/wp-content/uploads/2017/09/Strategy-and-quant_executive-summary_050917.pdf`

Oler, D., Harrison, J. S., & Allen, M. R. (2007). Over-interpretation of short-window event study findings in management research: an empirical illustration. *Available at SSRN 665742*. doi: http://dx.doi.org/10.2139/ssrn.665742

Park, J. W., & Lee, C. W. (2018). Performance of stock price with changes in sri governance index. *Corporate Social Responsibility and Environmental Management*, *25*(6), 1121–1129. doi: https://doi.org/10.1002/csr.1526

Park, N. K. (2004). A guide to using event study methods in multi-country settings. *Strategic Management Journal*, *25*(7), 655–668. doi: https://doi.org/10.1002/smj.399

Ross, S. A. (1977). The determination of financial structure: the incentive-signalling approach. *The bell journal of economics*, 23–40. doi: https://doi.org/10.2307/3003485

Scholes, M. S. (1972). The market for securities: Substitution versus price pressure and the effects of information on share prices. *The Journal of Business*, *45*(2), 179–211. Retrieved from `https://www.jstor.org/stable/2352030`

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), 425–442. doi: https://doi.org/10.1111/j.1540-6261.1964.tb02865.x

Shleifer, A. (1986). Do demand curves for stocks slope down? *The Journal of Finance*, *41*(3), 579–590. doi: https://doi.org/10.1111/j.1540-6261.1986.tb04518.x

Spence, M. (1973). Job market signaling. *The Quarterly Journal of Economics*, *87*(3), 355–374. doi: https://doi.org/10.2307/1882010

Stanley, M. (2016). *The gender advantage: Integrating gender diversity into investment decisions.* Retrieved from https://www.morganstanley.com/pub/content/dam/msdotcom/ideas/gender-diversity-toolkit/Gender-Diversity-Investing-Primer.pdf

Talmor, E. (1981). Asymmetric information, signaling, and optimal corporate financial decisions. *Journal of Financial and Quantitative analysis*, 413–435. doi: https://doi.org/10.2307/2330363

UN. (2004). The global compact leaders summit: Final report. *Global Compact Office, New York*. Retrieved from https://www.unglobalcompact.org/library/255

Zou, P., Wang, Q., Xie, J., & Zhou, C. (2019). Does doing good lead to doing better in emerging markets? stock market responses to the sri index announcements in brazil, china, and south africa. *Journal of the Academy of Marketing Science*, 1–21. doi: https://doi.org/10.1007/s11747-019-00651-z

Appendix

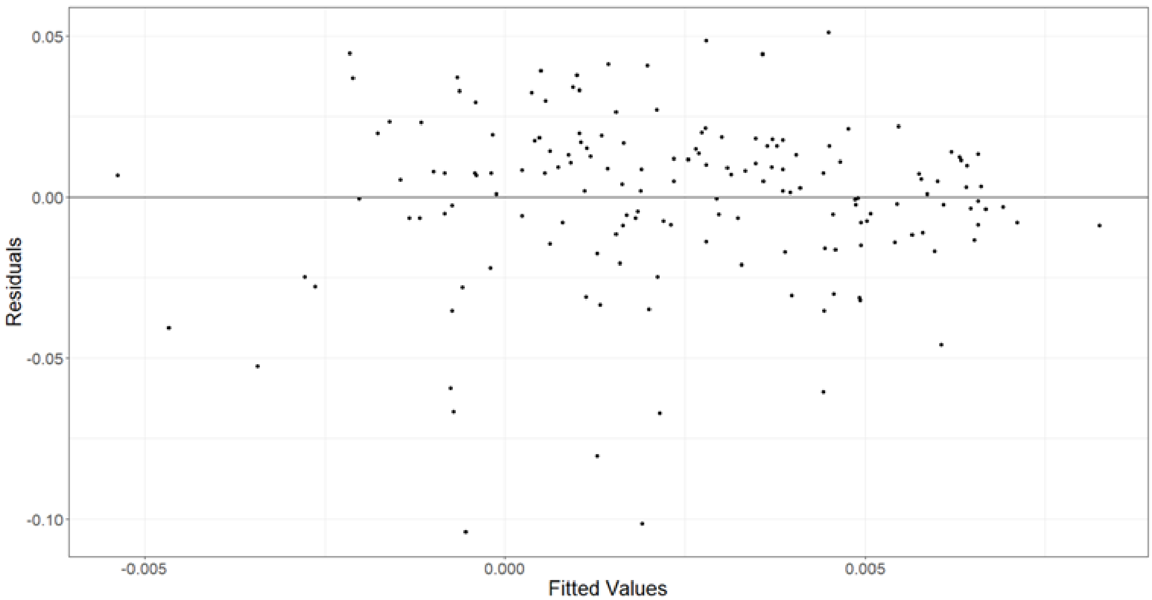
A1 Empirical findings and results

Table A1.1: Descriptive statistics of raw data

	Min	1st quartile	Median	Mean	3rd quartile	Max	NA	N
CAR[0:3]	-12.47%	-0.73%	0.56%	0.19%	1.81%	7.32%	0	172
Mcap	1.15e+09	4.01e+09	1.40e+10	2.65e+10	3.88e+10	2.51e+11	0	172
P/B	-39.25	1.11	1.75	3.11	2.88	72.810	4	168
D/E	-732.71%	42.81%	102.84%	169.50%	222.68%	1531.97%	3	169
ROA	-22.53%	0.95%	3.26%	4.52%	6.14%	42.47%	8	164

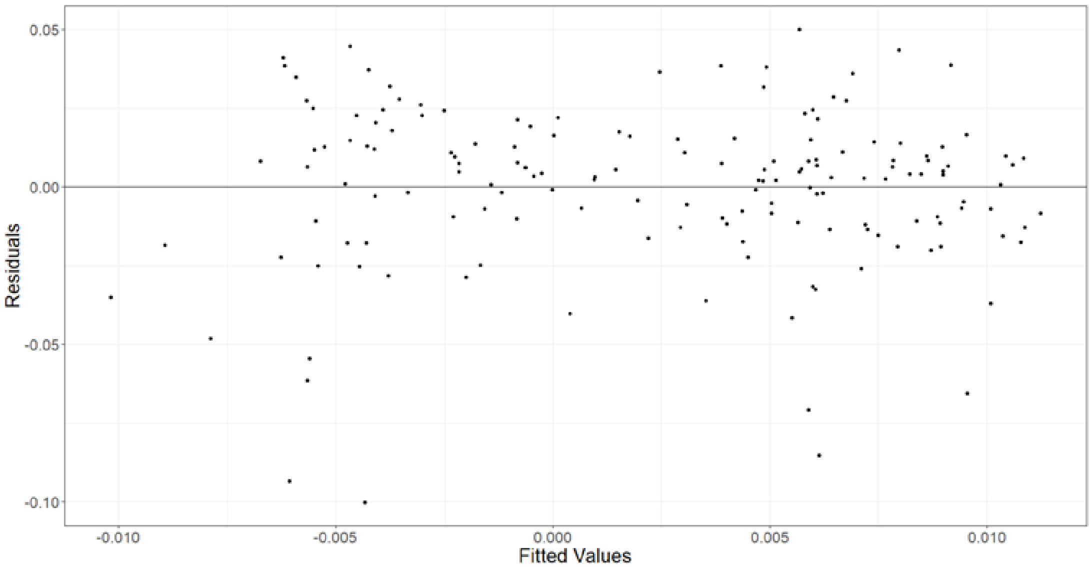
Note: This table presents descriptive statistics of the raw variable data used in the cross-sectional analysis.

Figure A1.1: Regression (1) residuals plotted against fitted values



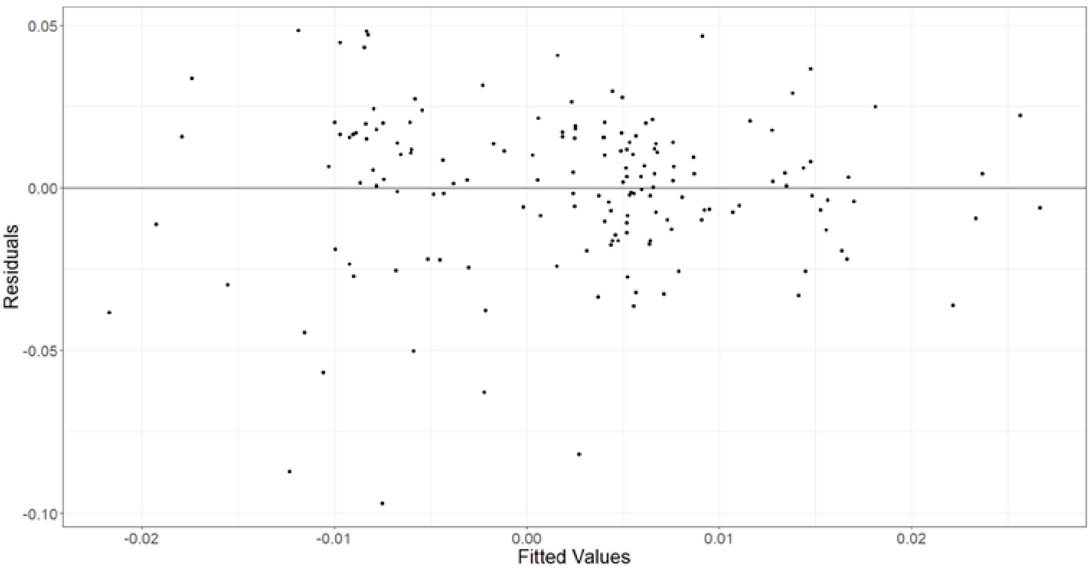
Note: This figure tests for heteroscedasticity in regression (1) by plotting residuals against fitted values.

Figure A1.2: Regression (2) residuals plotted against fitted values



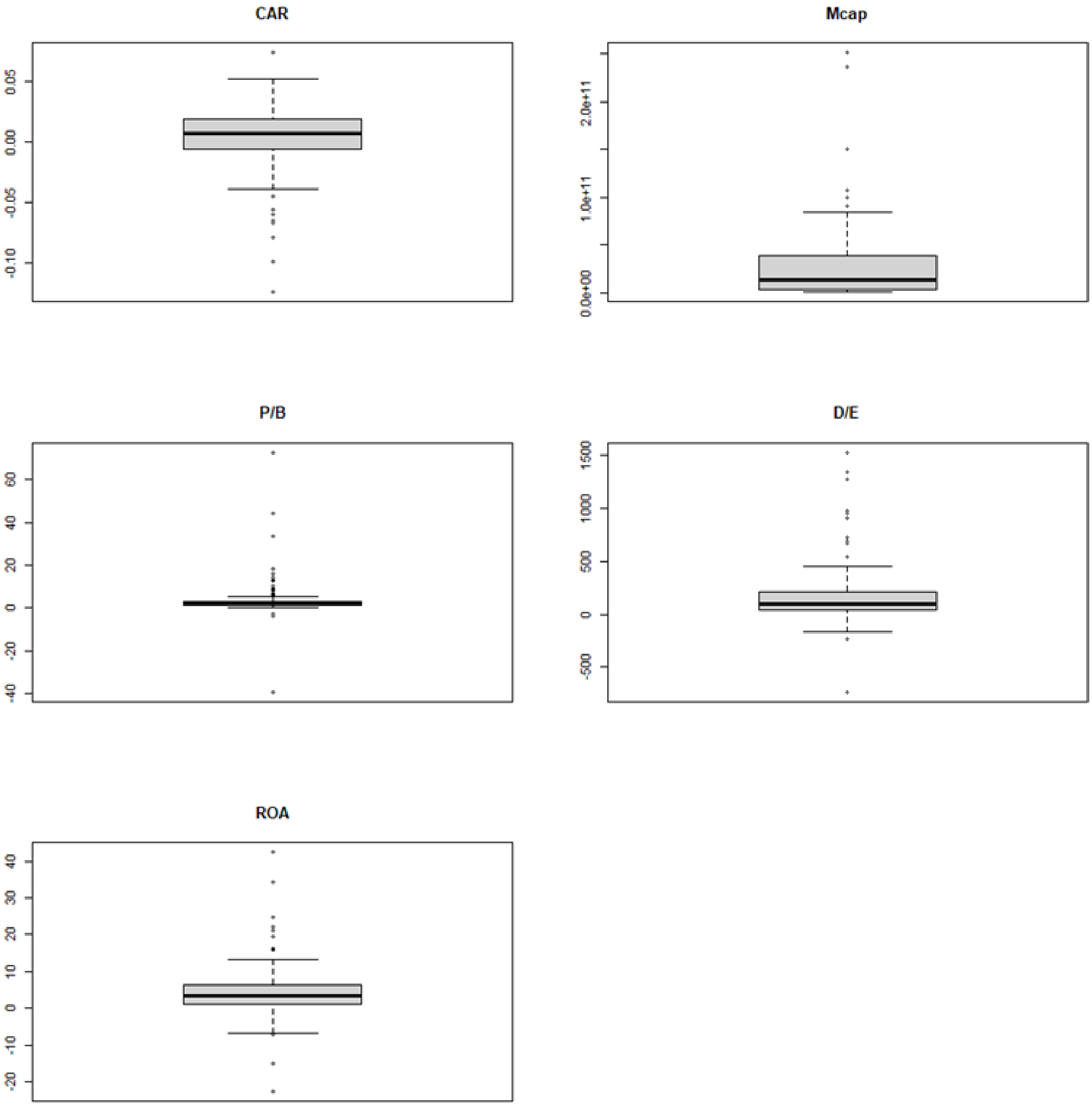
Note: This figure tests for heteroscedasticity in regression (2) by plotting residuals against fitted values.

Figure A1.3: Regression (3) residuals plotted against fitted values



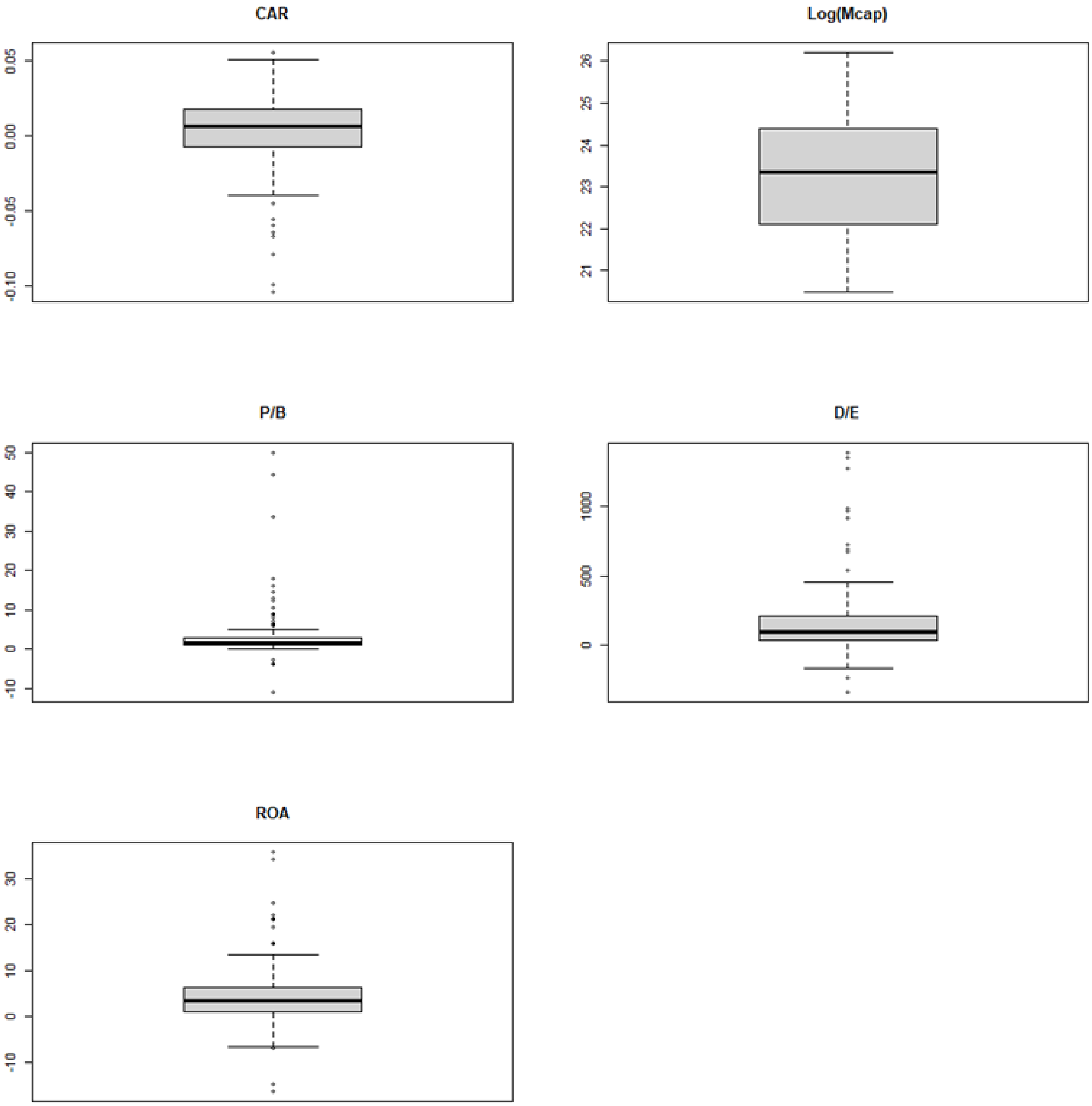
Note: This figure tests for heteroscedasticity in regression (3) by plotting residuals against fitted values.

Figure A1.4: Boxplot of cross-sectional variables before pre-processing



Note: These figures display raw data of cross-sectional variables before winsorizing and log-transformation.

Figure A1.5: Boxplot of cross-sectional variables after pre-processing



Note: These figures display data of cross-sectional variables after winsorizing and log-transformation.

Table A1.2: Robustness check 200 trading days

		2016-2018		2019		2020		2016-2020	
				All Regions					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.032%	-0.145	0.124%	0.507	0.380%	1.672	0.180%	1.314
Short	[0:3]	-0.004%	-0.012	0.402%	1.163	0.130%	0.404	0.193%	0.999
Long	[0:10]	-0.826%	-1.549	1.279%	**2.230****	0.360%	0.675	0.381%	1.188
Full	[-2:10]	-0.858%	-1.482	1.402%	**2.250****	0.739%	1.276	0.560%	1.608
				AM					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	0.367%	1.211	0.239%	0.677	0.901%	**1.950***	0.483%	**2.219****
Short	[0:3]	-0.248%	-0.580	-0.290%	-0.581	-0.628%	-0.960	-0.382%	-1.239
Long	[0:10]	-0.489%	-0.688	2.571%	**3.104*****	0.065%	0.060	0.852%	1.670
Full	[-2:10]	-0.122%	-0.158	2.810%	**3.120*****	0.967%	0.820	1.336%	**2.406****
				EU					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.474%	-0.903	-0.217%	-0.461	0.621%	**2.263****	0.162%	0.726
Short	[0:3]	-0.344%	-0.463	1.215%	**1.828***	0.652%	1.680	0.650%	**2.058****
Long	[0:10]	-1.100%	-0.894	-0.434%	-0.394	0.599%	0.930	-0.029%	-0.056
Full	[-2:10]	-1.575%	-1.180	-0.651%	-0.543	1.220%	**1.743***	0.133%	0.233
				A/P					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.292%	-0.709	0.402%	0.870	-1.537%	**-2.553****	-0.347%	-1.233
Short	[0:3]	0.764%	1.314	0.463%	0.709	-0.001%	-0.066	0.420%	1.055
Long	[0:10]	-1.134%	-1.181	1.437%	1.327	0.162%	0.114	0.256%	0.388
Full	[-2:10]	-1.431%	-1.365	1.838%	1.562	-1.376%	-0.896	-0.091%	-0.126

*Note: This table presents cumulative average abnormal return (CAAR) over different time periods and regions using 200 trading days in the estimation window. Significance: *p<0.10, **p<0.05, ***p<0.01.*

Table A1.3: Robustness check 100 trading days

		2016-2018		**2019**		**2020**		**2016-2020**	
				All Regions					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.030%	-0.134	0.135%	0.509	0.349%	1.393	0.168%	1.161
Short	[0:3]	0.007%	0.220	0.376%	1.008	0.082%	0.240	0.185%	0.905
Long	[0:10]	-0.704%	-1.327	1.305%	**2.106****	0.348%	0.615	0.418%	1.233
Full	[-2:10]	-0.734%	-1.274	1.439%	**2.137****	0.686%	1.113	0.586%	1.589
				AM					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	0.358%	1.235	0.304%	0.804	0.820%	1.604	0.484%	**2.071****
Short	[0:3]	-0.199%	-0.484	-0.283%	-0.530	-0.883%	-1.205	-0.442%	-1.340
Long	[0:10]	-0.595%	-0.874	2.706%	**3.053*****	-0.011%	-0.009	0.848%	1.548
Full	[-2:10]	-0.236%	-0.319	3.010%	**3.123*****	0.821%	0.621	1.331%	**2.236****
				EU					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.437%	-0.788	-0.247%	-0.480	0.587%	**2.072****	0.142%	0.595
Short	[0:3]	-0.150%	-0.191	1.200%	1.642	0.707%	**1.766***	0.708%	**2.102****
Long	[0:10]	-0.552%	-0.424	-0.297%	-0.245	0.511%	0.769	0.067%	0.120
Full	[-2:10]	-0.989%	-0.699	-0.544%	-0.414	1.097%	1.520	0.210%	0.350
				A/P					
Interval	Length	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat	CAAR	T-stat
Pre	[-2:-1]	-0.304%	-0.779	0.377%	0.769	-1.551%	**-2.595****	-0.365%	-1.278
Short	[0:3]	0.761%	1.379	0.367%	0.530	-0.001%	-0.019	0.391%	0.969
Long	[0:10]	-1.105%	-1.142	1.112%	0.974	0.554%	0.395	0.264%	0.394
Full	[-2:10]	-1.349%	-1.356	1.495%	1.197	-0.997%	-0.654	-0.101%	-0.139

*Note: This table presents cumulative average abnormal return (CAAR) over different time periods and regions using 100 trading days in the estimation window. Significance: *p<0.10, **p<0.05, ***p<0.01.*