DOES THE BOND MARKET FULLY REFLECT THE VALUE OF INTANGIBLES?

A BOND MARKET EVENT STUDY ON EMPLOYEE SATISFACTION

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Does the bond market fully reflect the value of intangibles? *A bond market event study on employee satisfaction*

Abstract

This paper examines how the bond market reflects the value of an intangible, more specifically the value of employee satisfaction. Prior research has found support for a mispricing of information on employee satisfaction in the equity market. As stocks and bonds are contingent claims on the same underlying cash flows and firm value, the same information would be expected to affect the valuation of both securities. Thus is of interest to understand whether this finding extends to the bond market. For this purpose, an event study approach was adopted to capture both the short-term and long-term reaction to the announcement of Fortune Magazine's '100 Best Companies to Work For' list in the US. The list is a highly public and salient measure of employee satisfaction and comprises an output measure on the quality of an intangible: human capital. The sample comprises 353 firm-year observations on the announcement of the list on 78 firms over the period 2003-2021. We find no statistically significant abnormal returns to the announcement of the list. The results are evident both in the short horizon and the long-run horizon. We offer multiple interpretations for this but argue that the most plausible explanation is that higher employee satisfaction as indicated by list inclusion is immediately incorporated in bond prices. This because bond investors perceive high employee satisfaction as a valid signal on the risk profile and financial capability of the firm. We attribute the contradiction of our findings with the ones in the equity market to the difference in pay-off structure between bondholders and equity holders – where bondholders are more concerned with limiting the downside risk.

Keywords:

Event study, bonds, intangibles, human capital, employee satisfaction

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Definitions

Public debt: Public debt, also called outside debt, is here referring to corporate debt that has been issued to the public and is traded on an open market. Outside refers to the fact that debtholders rely on publicly available information produced either by the firm itself or other information purchased by the firm (e.g. ratings, third-party audits, etc.) or other information publicly available (Fama, 1985). Publicly traded bonds, commercial papers, etc. are public debt.

Private debt: Private debt, also called inside debt, is here referring to a corporate debt contract where the debtholder gets access to information from an organization's decision process not otherwise publicly available. Regular bank loans are private debt or other debt classified as private placement (Fama, 1985). The distinction is similar to that on private and public equity.

Debt covenant: A covenant is a legally binding contractual obligation within the debt agreement contract between a bond issuer and a bondholder which limits the actions of the issuer. It is intended to protect the interests of both parties. A common covenant for example is limitations on mergers and acquisitions.

Intangible assets: An intangible asset is an identifiable non-monetary asset without physical substance. Goodwill, brand recognition and intellectual property, such as patents, trademarks, and copyrights, as well as other non-balance sheet asset such as human capital are all examples of intangible assets.

Anomalies: The literature has provided empirical evidence for several factors that explain average returns in assets. Because these factors cannot be explained by the classical capital asset pricing model (CAPM) they have typically been called anomalies in asset pricing literature (Fama & French, 1996).

Multifactor model: A multifactor model is a financial model that uses multiple factors in its calculations to explain market phenomena and/or equilibrium asset prices. These models generally include systematic factors, which then explain the average returns several risky assets.

Abbreviations

The Best Companies to Work For (BCs): A company that has appeared on Fortune Magazine's list '100 Best Companies to Work For in America'.

Abnormal Return (AR): The difference between the actual realized return earned on a security and the expected return (often referred to as "normal" return). The expected return is an estimated return earned on the security should a given event not have happened.

Average Abnormal Return (AAR): Average Abnormal Return refers to the cross-sectional average of the abnormal returns on a given point in time, often a day. It is a cross-sectional aggregation of abnormal returns.

Cumulative Abnormal Return (CAR): Cumulative Abnormal Return refers to the sum of abnormal returns over a given period of time. It is a time-series aggregation of abnormal returns.

Cumulative Average Abnormal Return (CAAR): Cumulative Average Abnormal Return refers to the sum of average abnormal returns over a given period of time. It is a time-series aggregation of cross-sectional abnormal returns.

Standardized Abnormal Return (SAR): Standardized Abnormal Return refers to an adjustment where each observation of abnormal return is weighted in proportion of the standard deviation of the estimated abnormal return.

Trade Reporting and Compliance Engie (TRACE): Trade Reporting and Compliance Engine (TRACE) is a program developed by the National Association of Securities Dealers (NASD), now known as FINRA, that allows for the reporting of over-the-counter (OTC) transactions pertaining to eligible fixed-income securities. Brokers, who are FINRA members and deal with specific fixed-income securities, are required to report their transactions by the Securities and Exchange Commission (SEC) rules.

Financial Industry Regulatory Authority (FINRA): The Financial Industry Regulatory Authority (FINRA) is a private American corporation that acts as a self-regulatory organization that regulates member brokerage firms and exchange markets. FINRA is the successor to the National Association of Securities Dealers (NASD) as well as the member regulation, enforcement, and arbitration operations of the New York Stock Exchange. It falls under regulatory supervision of the Securities and Exchange Commission (SEC).

1. **Introduction**

Few areas within accounting and finance have received as much attention as anomalies in capital markets' ability to fully incorporate market information into security prices (Kliger & Gurevich, 2014; Kothari & Warner, 2007; MacKinlay, 1997). With the rise of the human capital intense firm (Zingales, 2000) particular attention has been spent on the market's ability (and evident inability) to incorporate the value of intangibles into security prices (e.g. Aboody & Lev, 1998; Chan et al., 2001; Lev & Sougiannis, 1996). The theoretical foundation has it that if markets are efficient and prices reflect all available information, the potential benefits of intangibles are incorporated to reflect a higher current price – therefore limiting any excess (or abnormal) future returns.

Yet existing research has focused exclusively on the equity market with virtually none on the other main market for providing capital to the firm, the bond market. Concentrating on the publicly traded corporate bond market is also theoretically motivated as stocks and bonds are contingent claims on the same underlying cash flows and firm value (F. Black & Scholes, 1973; Merton, 1974)Therefore, common information would be expected to affect the value of both securities.

Consequently, this paper aims to examine whether the mispricing of intangibles reported in equity markets extends to the bond market and thus *how the bond market reflects the value of intangibles.* To address this question, we examine the bond market's value of human capital and more specifically investigate it through employee satisfaction.

Human capital theories and empirical findings, both suggests that employee satisfaction is beneficial for firm value. It benefits the firm by decreasing various labor related risks (Bradford, 2004; Karpoff & Lott, 1999), lowering risk of product failure (Fehr & Gächter, 2000; Rabin, 1993), increasing operational and financial performance Huselid (1995) and reduces cash flow volatility (Chen et al., 2019) - to mention a few. Previous studies, drawing on screening theory have highlighted that good employee relations are rewarded by private debtholders with a lower cost of debt and that there is a negative relationship between high employee satisfaction and cost of debt (Chi & Chen, 2021; Francis et al., 2019; Qian et al., 2021).

These above studies all examine, mostly, the pricing of private debt. At the same time, previous research has presented evidence on the equity market's inability to incorporate employee satisfaction into security prices (Edmans, 2011; Edmans et al., 2014; Filbeck & Preece, 2003; Fulmer et al., 2003). The information setting, relating to the information available, in which public debtholders, in contrast to private debtholders, find themselves allow for more information asymmetry. In either case both markets should ultimately be occupied with evaluating the cash flow generating ability of the firm (Black & Scholes, 1973; Merton, 1974).

Whether the bond market follows the same suit as private debtholders and incorporates employee satisfaction as a proxy for human capital quality into debt pricing, or if it fails to do so, as the literature has shown the equity markets to do, still remains an open empirical question. Which outcome is borne out in reality is important in order to further understand the wealth effect between different capital providers.

This is investigated by studying the bond market's reaction to the announcement of Fortune Magazine's '100 Best Companies to Work For in America' list over the years 2003-2021. The list is a public and highly salient measure of employee satisfaction and if markets are efficient and prices reflect all available information the potential benefits of employee satisfaction is incorporated to reflect a higher current valuation - limiting any excess return (also abnormal return). We empirically test this by observing the short and long-run horizon returns by using an event study research design

There appears to be some evidence of an initial lack of reaction on the announcement day, leading up to the announcement and cumulative abnormal return over the event window, as evidenced by finding abnormal returns. However, these returns do not remain when controlling for firm and bond specific characteristics. This would suggest that other factors than the announcement of the list is explaining the abnormal returns, and that the benefit of high employee satisfaction is reflected in prices in the bond market.

The long-run returns after the announcement of the list, 1-12 months, do not show any evidence of a correction as evidenced by finding no abnormal returns. This further supports the above results that information on high employee satisfaction is reflected in prices by the bond market. Additionally holding an equally weighted portfolio of bonds issued by BCs over the sample period with yearly rebalancing when a new list is announced did not yield any statistically abnormal performance compared to two matching portfolios on rating and industry.

Our results are robust to further testing of firms with financial constraints and more serious agency issues, which have been shown to be situations when employee satisfaction is not beneficial for debtholders (Chen et al, 2019). Controlling for bond IPO-underpricing, any influencing effect from bonds maturing closely to the announcement of the list as well as alternative measures of firm-specific controls the results remain robust. Finally, exploring if any ranking attributes of the list are influencing our results, we control for firms appearing on the list for the first time and top ranked firms, but the results stand.

This indicates that the bond market either i) reflects the potential benefit of employee satisfaction into bond prices or ii) does not value employee satisfaction as it has no benefit to firms' ability to repay debt obligations. The latter would seem unlikely given the importance of employees in the rise of the human capital intense firm (Zingales, 2000), in addition to the literature presenting ample evidence of several benefits of employee satisfaction relating to both operational performance, decreased risk and cash flow volatility. Our results would therefore suggest support for i).

We attribute the differing interpretation of the same information by the bond market and equity market to the difference in the pay-off structure between the two capital providers as debtholders carries a fixed claim on the firm's net assets. Debtholders thus are more concerned with downside risk. Overall shareholders, as the residual claimants, would lose out when investors reconsider their risk assessments downward, whereas bondholders, as holders of a senior claim, benefit from a decrease in risk evaluations (Kliger & Sarig, 2000). Equity holders might still value the benefits of employee satisfaction, however, it only affects value when it manifests in subsequent tangible outcomes (e.g. earnings announcement) as argued by Edmans (2011).

The findings in this study makes two contributions. It has highlighted a difference in how capital providers values an intangible, human capital. This contributes to furthering our understanding on the wealth effect between different capital providers. In particular when considering size and importance of the corporate bond market in providing capital. Secondly, it expands on previous literature supporting evidence that bondholders pay attention to employee satisfaction and incorporates its benefit into debt prices. By doing so has shed further light on how bondholders view the trade-off between the costs and benefits of employee friendly treatment, especially in a public market setting where information asymmetry is higher than a private information setting.

The thesis is structured as follows. Section 2 introduces the readers to the unique characteristics of the bond market. Section 3 discusses the theoretical link between employee satisfaction and bond returns, and the connecting hypothesis formulation. Section 4 presents the study's methodology and discusses methodological considerations. Section 5 and 6 presents the results. In section 7 we discuss the findings and possible explanations for our findings while section 8 .

2. Introduction to corporate bonds and bond market characteristics

The bond market plays an important role in the global financial markets and reached a market value of $124 trillion capital by the end of 2020, implying that it is an even larger market than the equities market ($ ~106 trillion). The US bond market represented 38% of the global value outstanding as of 2020 and has grown at a CAGR of ~8% during 2010-2020. Several different security types are traded on the fixed income market, including municipality bonds, treasury, mortgage-backed bonds, federal agency securities and asset backed bonds, whereof corporate bonds represented ~20% of the issued amount in the US in 2020. The average issue size for corporate bonds between 2006-2020 amounted to $ ~800 million (SIFMA, 2022).

In addition to the initial issuance, there is a secondary market for bonds where trade occurs once bonds have been issued in the primary market. Bonds can then trade either over the counter, or on regulated exchanges. In contrast to equities, bonds most commonly trade over-the-counter (OTC). Trading OTC implies that the trade is not monitored by, or subject to, rules of major exchanges, but the trade is executed bilaterally between parties. Even when bonds issued are traded on a regulated exchange, the following trading typically takes place over-the-counter. Over-the-counter trading is typically characterized by larger average trade sizes compared to the regulated exchanges. Furthermore, in contrast to the equity markets where trading activity is spurred by the existence of individual investors, the bond market is dominated by institutional investors such as mutual funds, pension funds and insurance companies. These institutional investors commonly pursue long-term buy-and-hold strategies, why bonds trade less frequently compared to equities, which in turn results in a lower overall liquidity of the market (Bai et al., 2019). It is more common for bonds to not trade than to trade (Bessembinder et al., 2009). The high degree of OTC trading also explains the lower level of transparency in the bond market compared to the equity markets.

With regards to bonds as a security type, these can be defined as a type of debt instrument that pay a fixed rate of interest over a predetermined period. Bonds have four main characteristics, including the term to maturity, the issuer, the principal (or face value) and coupon rate. The term to maturity represents the number of years for which the owner will receive interest payments, and after which the issuer will repay the obligation. The issuer refers to the borrower, which in the case of corporate bonds are the corporations. The principal of a bond refers to the amount that the issuer repays the bondholder on the maturity date, and the coupon rate is the contractually agreed annual interest that the bondholder should expect to receive while holding the bond (Choudhry, 2004).

On the one hand, stocks and bonds are both contingent claims for cash flows of the firm. The fortune of both stock and bond investors depends on the same firm value, and hence both are exposed to volatility shocks. On the other hand, they differ with regards to several factors, such as the aforementioned contractual situations, risk characteristics as well as investor group. Bond investors have a limited upside and are more sensitive to the downside risk of the firm, why bonds are considered a more conservative investment associated with lower volatility and risk premium (Chung et al., 2019). Between 2003-2021, the average return for US Baa-rated corporate bonds (investment grade) has been 7%, which can be compared to an average annual return of 13% for the S&P 500 for the same period (Damodaran, n.d.). However, the volatility and risk compensation for bonds differ greatly between rating classes and an inverse relationship exists between bond ratings and interest rates. Credit ratings broadly fall into two categories, investment-grade (BBB- rating and above) and non-investment grade (ratings below BBB-). The higher the credit rating, the less sensitive to interest rate changes and lower volatility and vice versa (Heinke, 2006).

3. Literature review and theory

The following section describes theoretical concepts and previous research related to this paper, including studies related to the link between employee satisfaction and firm performance, prior event studies on the pricing of employee satisfaction in equity markets, employee satisfaction in private debt markets and bond market efficiency. The aim is providing a context to the study, as well as highlighting the gap in previous research which we aim to fill, which leads to the hypothesis formulation.

3.1. Literature review & theoretical framework

3.1.1. Human capital theory and the effect of employee satisfaction on firm performance

"In the past the man has been first; in the future, the system must be first"

(Taylor, 1911)

In past times, conflicting beliefs prevailed to whether employee satisfaction should be considered a source of value creation for firms. Traditional theories (e.g., Taylor, 1911) focused on cost efficiency argue that firms should strive to maximize output while minimizing the input costs. Because employees are viewed as any other input good to the firm, employee satisfaction is a sign of managerial inefficiency (indicating that employees have either underworked or are being overpaid) that decreases firm value. These theories are in line with the shareholder theory introduced by Friedman (1970), stating that corporations' sole focus should be on their shareholders and to maximize profits.

The stakeholder theory later presented by Freeman (1984) challenges the traditional shareholder perspective and suggests that the responsibility of a firm extends beyond its shareholders. Corporations are responsible for all parties who are affected by the welfare of the firm. Donaldson & Preston (1995) expanded on the stakeholder theory, claiming that activities undertaken to enhance the value for one stakeholder group are not necessarily conducted on the expense of other stakeholders, but rather can increase firm value to the benefit for all stakeholders. On this line, human relations theories have also evolved that takes an opposing angle on the traditional view on employee satisfaction. In contrast to traditional manufacturing firms during the 20th century, the output of the modern firms is often more complex to measure and reward (Kohn, 1993). To a higher degree, the output of employees' work is intangible and thereby harder to quantify, such as customer and supplier relationships (Edmans et al., 2014). According to this new strand of research, the modern firm calls for another view on human capital, where employee satisfaction is not a result of wasteful management of resources by the firm, but should be viewed as an investment in key organizational assets (Maslow, 1943; Herzberg, 1959).

As employees are more prone to staying at firms where they feel satisfied, employee satisfaction should improve retention and facilitate recruiting (Chen et al., 2019). The efficiency wage hypothesis further states ways through which employee satisfaction can improve motivation at the workplace (Akerlof & Yellen, 1986). Employees who feel satisfied with their workplace, feel obligated to give back to their employer by committing increased effort in their work (Akerlof, 1982). From the perspective of sociological theory, satisfied employees will internalize the objectives of their employer, and thereby have incentives to induce greater effort (MacGregor, 1960)

Several studies have been devoted to assess whether employee satisfaction influences operational performance (e.g., Huselid, 1995; Ichniowski & Shaw, 1999), with findings indicating that employee satisfaction is beneficial for a firm's operational performance in several dimensions. Satisfied employees are less likely to participate in labor strife, and thus reduces the risk that the firm faces legal and reputational costs due to employee litigation (Bradford, 2004; Karpoff & Lott, 1999). In line with sociological theory stating that satisfied employees will internalize their employer's objectives, satisfied employees are also less likely to commit sabotage, resulting in a lower risk of product failure (Fehr & Gächter, 2000; Rabin, 1993).

These aspects, together with a lower employee turnover, causes firms with high employee satisfaction to minimize operational disruptions, which in turn, translates into higher productivity and lower cash-flow volatility (Chen et al., 2019). Faleye & Trahan (2011) investigates multiple dimensions of operating performance including employee productivity, firm-level productivity, and profitability, and finds that firms with high employee satisfaction outperforms their benchmarks on all dimensions. These results are also in line with Huselid (1995) who finds that firms committed to good practices of human resource management benefit from higher profitability.

If the traditional understanding of human capital holds, investments in employee satisfaction would decrease firm value. However, this view has been succeeded by a modern view provided by recent human capital theories and empirical findings, suggesting that employee satisfaction is beneficial for firm value. The introduction to human capital theory hence provides a fundamental understanding for its' implications for firm value, performance and risk, which, in extension, should be reflected in the bondholders' view of firms.

3.1.2. Incorporation of employee satisfaction in (efficient) equity markets

Examining other intangibles similar to employee satisfaction firms with high R&D (Chan et al., 2001; Lev & Sougiannis, 1996), advertising (Chan et al., 2001), patent citations (Deng et al., 1999), and software development costs (Aboody & Lev, 1998) all earn excess long-run returns. The main explanation offered to the previous results for why intangibles are not fully incorporated into prices is that the market lacks information on their value, the so called "lack-of-information" hypothesis.[1]

Building further on the tension caused by the ambiguous predictions of whether employee satisfaction is beneficial for firm value, several studies have also explored the market's incorporation of employee satisfaction (e.g., Edmans, 2011; Faleye et al., 2006; Fulmer et al.). These studies all rely on the theoretical foundation of the theory of an efficient market and thus tests the efficient market hypothesis (in its semi-efficient form).[2] If markets are efficient, and reflect all available information, the potential future benefits of employee satisfaction should be reflected in higher valuations and thereby limit any excess future returns. Consequently, for employee satisfaction to yield excess returns, human relations theories' prediction on its effect on firm value must be true, namely that it is beneficial for firm value. Secondly, these benefits must not immediately be capitalized by the market.

One of the more important contributions in this field was made by Edmans (2011) who investigated the relationship between employee satisfaction and long-run stock returns.[3] By constructing a value-weighed portfolio of Fortune Magazine's list "100 Best Companies to Work for in America", Edmans demonstrate an annual four-factor alpha of 2.1% above a matched industry benchmark for the portfolio from 1994 to 2009. These firms also show more positive earnings surprises, indicating that only when an intangible subsequentially manifest in tangible outcomes is it incorporated into stock prices. Controlling for various industry and firm characteristics the results stand, as well as after exploring alternative explanations such as SRI-funds raising prices due to firms' list inclusion. Using the list addresses the "lack-of-information" argument as it is a highly salient and publicly visible information source on the value of an intangible with a clear announcement point. Edmans concludes[4] *"…[the conclusion] of the paper still remains […] the market's failure to incorporate the contents of a highly visible measure of intangibles"*

Other studies have used the same method to test for the market's incorporation of employee satisfaction, which have yielded different results. Two of the first studies using

1 Spending on R&D, for example, can be observed but is an input measure that lacks information of its quality or success (Lev, 2004). Even if an measure is available its information might be overlooked by the market if it is not salient (Edmans, 2011).
2 The weak form of market efficiency states that security prices reflect information embedded in historical prices, and the semi-strong form claims that security prices reflect all publicly available information, including information in past prices. Finally, the strong form asserts that security prices reflect all information, including private and publicly available information (Fama, 1991)
3 Edmans (2011) tests the market's long-run efficiency by forming his portfolios one month after list publication. This gives the market ample time to react to the information.
4 Mis-pricing explanations for the positive returns found by Edmans (2011) are still subject to reverse-causality, i.e., that profitability would drive high employee satisfaction, and omitted variables concern, i.e. that employee satisfaction is acting as a proxy for other variables, e.g. good management, causing higher stock returns. However, Edmans points out that the conclusion of the markets failure to incorporate the list-information into prices remains.

the “100 Best Companies to Work for in America” list was Filbeck and Preece (2003), and (Fulmer et al., 2003). The former study found a statistically significant abnormal return on the announcement date, but no differences in long-term returns between the list companies and the benchmarks, while the latter found that the companies included in the list outperform the market when considering cumulative returns, but not consistently for annual returns. More recent results are consistent with the ones by Edmans (2011). Faleye, O., Trahan, E., (2006) finds that investors react positively to the list’s announcement, and that firms included in the list outperform its benchmarks. Finally, Boustanifar & Kang (2022) extends the study by Edmans (2011) to include eleven additional years of data and control for not previously tested exposure to risk factors. Their results show that companies included in the “100 Best Places to Work for in America” list continues to earn an excess return of 2-2.57% per year, hence suggesting the market’s tendency to undervalue intangibles persist over time. This seems paradoxical given that anomalies tend to disappear after publication (Bebchuk et al., 2013; Mclean & Pontiff, 2016).

The above studies all confirm the link between employee satisfaction and firm value and highlight the market’s inability to incorporate these future benefits, which in turn yields excess returns. Predominantly research on intangibles and market reaction has exclusively focused on equity markets. Naturally the question of the extension of the above anomaly of employee satisfaction to other financial markets and sources of firms’ financing arises (Boustanifar & Kang, 2022), namely the corporate bond market. Employee satisfaction should also matter to the bond market as debt is serviced out the firm’s operating cash flow, which according to human capital theories should increase as a second order effect of higher employee satisfaction.

3.1.3. The pricing of bonds and credit spread components

Since this paper aims to explore whether the mispricing of intangibles reported in equity markets extends to the corporate bond market, it is important to understand the fundamental dynamics of bonds and the determinants of bond prices.

Merton (1974) suggests that the value of a corporate bond depends on three distinct parts: the required rate of return on risk-free debt, the provisions in the indenture, including maturity, seniority in the event of default, coupon rate, call terms, and the probability of default. Furthermore, a central concept for the pricing of bonds is the yield to maturity (YTM), which is the internal rate of return that sets the present value of all future cash flows equal to the current bond price in the market (Choudhry, 2004). The extent to which the YTM exceeds the risk-free alternative, is called the credit spread. From the standpoint of so-called structural models of default, initiated by Black & Scholes (1973) and Merton (1974) credit spreads exist for two reasons. First, there is a risk of default, and second, the bondholder will only receive a part of the promised payments in the case of default, commonly known as the recovery value (Collin-Dufresne et al., 2001).

A number of factors are in turn implied in these two components, including the default-free interest rate, asset prices, the slope of the yield curve, and asset volatility. Structural models of default posit a negative relationship between the risk-free interest rate and the credit spread. This can be attributed to the fact that a higher interest rate environment is commonly associated with higher economic growth and an overall lower risk environment, resulting in a narrow credit spread. With regards to the slope of the default-free term structure, often denoted the yield curve, an increase in the slope implies an increase in expected short-term interest rates. A positively sloped yield curve is often associated with an increase in economic activity, which can in turn improve a firm's growth rate and thus decreases its default probability. Concerning the factor of asset prices, a negative relationship is expected between the firm's credit spread and asset value, as an increase in the asset value reduces the leverage ratio and thereby the risk of default. Finally, credit spreads are also sensible to volatility in the firm's asset value. High asset volatility implies a higher probability that the value of the firm's asset falls below the value of its debt (Landschoot, 2004).[5]

In addition to the components implied by the structural models of default, more recent literature has found that variables that theoretically should determine the credit spread, in practice have limited explanatory power of changes in credit spreads. The findings of Brown (2000) suggest that the majority of credit spread changes is due to non-credit-risk factors. First, the corporate bond market is less liquid than the government bond markets, which inhibit the frequency of trading of bond market participants (Lin et al., 2011). Because investors cannot continuously hedge their risk, they will demand a liquidity premium (Amihud & Mendelson, 1986; Lo et al., 2004). Second, if there exists discrepancy in corporate and government taxes, bond yields are likely to reflect this. Elton et al., (2001) studies the credit spread in terms of three components: expected loss, tax effect and risk premium, with findings suggesting that taxation has a larger impact on credit spreads than expected loss. Furthermore, Collin-Dufresne et al., (2001) finds that the default risk only explains 25% of variation in the credit spread, while the remainder is explained by factors independent of changes in liquidity and credit-risk, such as local supply and demand shocks.

3.1.4. Empirical evidence on bond returns and bond market efficiency

Considering the extension of the intangible asset anomalies documented in the equity market to the bond market it is important to consider similar literature dealing with the bond market and intangibles. However, to the best of the authors knowledge no prior

[5] The factors pertaining to the structural model factors affecting bond prices is based on the option pricing theories of Black & Scholes (1973 and Merton (1974). According to this the bondholder has written a put option from the equity holders, agreeing to accept the assets in settlement of the payment if the value of the firm falls below the face value of the debt. Given a firm with high asset volatility it is therefore more probable that the put option will be exercised resulting in higher credit spreads.

studies have investigated this. Therefore, we here aim to illustrate the current literature landscape on bond market efficiency and the prediction of bond returns.

Outside of the above-mentioned theoretical model, the structural model, explaining bond returns there has been important empirical evidence put forth on i) the bond markets efficiency compared to the equity market ii) several characteristics to risk with explanatory predictive power for bond returns iii) anomalies pointing to market inefficiency iii) Trading strategies to earn excess return above transaction costs.

*B*ond market efficiency

Previous research has demonstrated that the equity market does not immediately incorporate the benefits of employee satisfaction into share prices (Boustanifar & Kang, 2022; Edmans, 2011). Ascertaining the level of efficiency by which the bond market reflects information compared to the equity market is therefore of importance to form an understanding of how employee satisfaction might be valued by the bond market. However, empirical findings testing the efficiency on the corporate bond market have yielded mixed results. Katz (1974) was one of the first studies dedicated to exploring the price reactions on the corporate bond market and found a lag in price adjustments following bond rating reclassifications, implying that the bond market is slow to assimilate relevant information. Subsequent work by Weinstein (1977) contradicts this by failing to find evidence of market inefficiency when also examining the effect of rating changes on bond prices. In line with these findings, the result by Hotchkiss & Ronen (2002) demonstrates the ability of the US bond market to efficiently reflect information is similar to that of the equity market.

Furthermore, it is of interest to understand the efficiency of the bond market around certain events, here the literature has focused on earnings announcements. The results found by Defond & Zhang (2014) and Easton et al. (2009) suggests that bond prices react to bad earnings news on a timelier manner than good earnings news and does so on a timelier manner than the equities market. This would be consistent with the bond holder's asymmetric payoff structure implying a downside risk aversion. In addition, Defond & Zhang (2014) finds an initial overreaction from bondholders to bad news earnings which appears to be corrected following the earnings announcement.

Comparing the efficiency of the bond and equity market, the returns of the one that is more efficient should have a predictive power over the other. The study by Downing et al. (2009) tests this, with findings showing that there exists a lead-lag relationship between stock and bond prices when incorporating information. These results are in line with Chordia et al. (2017) who suggest that equity markets are first to reflect new information, indicating that equities lead bonds. However, conflicting evidence is found in the study by Hotchkiss & Ronen (2002), who claim that stocks do not lead bonds in reflecting firm-specific information.

Anomalies in the bond market

In equity markets, anomalies have been discovered with regards to intangibles (se e.g. Aboody & Lev, 1998; Deng et al., 1999; Lev & Sougiannis, 1996) and it is therefore necessary to understand whether these dynamics extend to the bond market. In an important paper Fama & French (1993) developed a multifactor model for predicting bond returns, consisting of three equity factors: a market factor, size and book-to-market equity ratio. [6] In addition, two bond market specific factors were identified to have explanatory power when estimating bond returns. These were the maturity risk factor, the difference between the monthly long-term government bond return and the one-month treasury bill rate; the default risk factor, the difference between the return of the market portfolio of corporate bonds and the monthly long-term government bond. Empirical research have identified a number of other anomalies in the bond market, some of them which are similar to those discovered among stocks, such as an accrual anomaly[7] (Bhojraj & Swaminathan, 2009), underpricing tendencies during initial public offerings and seasoned offerings of bonds (Cai et al., 2007) and a momentum anomaly[8], which is not just a symptom of equity momentum (Jostova et al., 2013).

Trading strategy

Based on the empirical evidence on anomalies in the bond market, it is of relevance for this study to understand the possibilities of drawing on bond market characteristics to form trading strategies, which are robust to transaction costs. Houweling & van Zundert (2017) explores whether size, risk, value, and momentum factors can be successfully implemented in bond portfolio strategies. They document significant and economically meaningful alphas for these factors in the corporate bond market, which are robust to transaction costs (Houweling & van Zundert, 2017). Furthermore, Correia et al. (2012) investigates the ability of credit markets to accurately reflect default information (risk) inherent in credit spreads. The authors find a significant lag in the market's incorporation of information on default, indicating that bond market inefficient and that there exist possibilities for excess return strategies. However, conflicting results are found by Chordia et al. (2017), who examines if corporate bond returns display similar return predictability as equities and whether the predictability permits for arbitrage opportunities in excess of trading costs. The findings indicate that profitability, asset growth, illiquidity, credit ratings and equity return predict bond returns, while other predictors, such as accruals, earnings surprises, and idiosyncratic volatility, do not. Controlling for

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[6] Their multifactor model for bond returns is an augmentation of their influential three-factor model for equities with two additional bond market factors.
[7] Corporate bonds issued by firms with high operating accruals underperform corporate bonds of firms with low operating accruals (Bhojraj & Swaminathan 2009).
[8] Momentum here refers to, in short, buying winners and selling (short) losers. For a more thorough explanation see the original paper on momentum by Jegadeesh & Titman (1993).

transaction costs however, the returns diminish, indicating that bonds are efficiently priced.

Contrasting stocks and bonds, they are theoretically, conditional claims on the same underlaying cash flows and firm value (Black & Scholes, 1973; Merton, 1974). Accordingly, common information would be expected to affect the value of both securities. The question is then one of, how does the corporate bond market price this information, as compared to the equity market.

The literature on the bond market provides ambiguous evidence on its ability to fully reflect available information. This is further put into question when, relating to employee satisfaction, examining the previous findings on the equity market (e.g. Edmans 2011). This coupled with the fact that the literature on the reaction in the bond market has yet to extend to the value of intangibles, further motivates this study.

3.1.5. Employee satisfaction in private debt financing

Information on firms' employee treatment practices is not only of importance for the equity market but also constitutes valuable information to debtholders, because of its effect on the borrower's credit risk. In their role as delegated monitors, banks and creditors make investments in costly due diligence processes to assess the creditworthiness and risk profiles of potential borrowers. During the due diligence process, borrowers' human resources practices are commonly reviewed, and factors such as union activities, benefits plan, pending disputes and employee contracts have been shown to being considered (Datta et al., 1999; Marsh & Shaiman, 2022).

There are several reasons why high employee satisfaction might lower the credit risk and thereby lower the price of debt charged by banks and creditors. First, fair treatment of employees leads to enhanced operational performance and reduces the income stream uncertainty of borrowers (Francis et al., 2019). Because it is difficult to imitate, firms with high employee satisfaction entrust firm-specific human capital to produce a competitive advantage (J. A. Black & Boal, 1994; Palmer & Wiseman, 1999).

Second, employee treatment is an important factor in determining a firm's financing policy. Firms dedicated to fair employee treatment typically allocate a large portion of their resources for this purpose and therefore have strong incentives to convey their commitment to honor the implicit contracts with their employees (Bae, 2011). Consequently, firms with favorable employee treatment policies usually maintain lower leverage, leading to a higher debt capacity, a lower risk of financial distress and lower costs of financial distress (Verwijmeren & Derwall, 2010). The findings by Verwijmeren & Derwall (2010) further show that these firms have a lower bankruptcy risk.

Third, engaging in employee friendly practices also reveals a firm's willingness to invest resources in human capital as a way of ensuring that the firm is equipped for future growth. Hence, it can also function as a tool of signaling, to convey information about the future value of the firm. In turn, it can help to reduce information asymmetry between the firm, and the less informed party - the lenders (Francis et. al., 2019).

With regards to the above mentioned aspects, borrowing firms concerned with their employee treatment practices have higher creditworthiness and lower firm-specific risk, which put them in a more favorable position to negotiate terms with lenders (Bauer et al., 2009; Francis et al., 2019). The result of this, as suggested by Francis et. al. (2019), is that firms committed to fair employee treatment policies benefit from lower loan prices. The most distinct cost reduction was found for firms operating in competitive industries, and for firms with high levels of intangible assets. These results are also in line with Chi & Chen (2021) who find that the cost of corporate borrowing is negatively associated with positive employee reviews. In addition to a lower cost of corporate borrowing, firms with higher levels of employee satisfaction also faces fewer financial covenants and receives higher credit ratings (Francis et al., 2019; Bauer et al., 2009), an often used indirect measure of the cost of debt.

However, there are also compelling reasons why high employee satisfaction may increase the price of debt charged by banks and creditors. Debtholders do not always benefit from strong employee treatment policies as these relations are costly. Investments in better working environment, pension plans, health and benefit plans all increase the financial burden, reduces the firm's operating flexibility, and ultimately weakens the ability to meet debt obligations (Faleye & Trahan, 2011). Hence, increased employee satisfaction does not benefit debtholders of firms facing financial constraints or in the case of firms with more profound agency problems (Chen et al, 2019). Additionally, debtholders and employees' utility functions would diverge in these situations, further explaining why debtholders might not reward high employee satisfaction. Especially since employees have a more senior claim on the firm's assets.[9]

The above literature has almost exclusively dealt with private debt. Public debt[10] and private debt share many common features. However, they differ markedly in certain aspects influencing the pricing of debt, justifying our purpose of examining public debt.

3.1.6. Employee satisfaction in public debt financing

Research on the effect of employee satisfaction on public debt financing is scarce. However, the way in which employee satisfaction influences the way debtholders treat borrowers should, in many ways, be similar in the setting of private and public debt. One

[9] Depending on the jurisdiction in question the preferential scheme order can vary, but employees usually carry a higher claim than debtholders.

[10] Public debt is also referred to outside debt. Outside referring to the fact that debtholders rely on publicly available information produced either by the firm itself or other information purchased by the firm (e.g. ratings, third-party audits, etc.) or other information publicly available (see Fama, (1985)). It also refers to the fact that public debt is publicly traded on an open market, i.e. a regulated exchange or OTC (over-the-counter).

of the studies conducted in the latter setting, thereby also one of the studies most similar to ours is by Chen et al., (2019). Their findings are in line with the ones made in private markets, namely that borrowers with sound employee treatment policies benefit from lower bond yield spreads. The results are also in line with the study by Bauer et al. (2009) who finds that firms with strong employee relations benefit from lower bond yield spreads, as well as higher bond ratings. As in the case of banks and creditors, Chen et al., (2019) find that bondholders incorporate the improvements in firm productivity, as well as reduced the risk of product failure, labor strife, and lower employee turnover resulting from high employee satisfaction.

However, our study differs from Chen et al., (2019) and Bauer et al. (2009) in that it investigates the market reaction to information on the value of an intangible and thus captures the bond market dynamics of the intangible value of human capital.

Moreover, when comparing bondholders and shareholders, it should be emphasized that they share different claims on the firms' net assets, leading to conflicting interests (Ahmed et al., 2002). Shareholders' claim is on the upside as they have a residual claim on the firms' net asset therefore having an unlimited payoff. Bondholders by contrast carries a fixed claim on the firms' net assets equaling its contractual debt obligations and thus does not share any excess payoff. If the firms' net assets fail to cover its contractual debt obligations the debtholder stand the risk of receiving less than the promised payments. Consequently due to this asymmetric payoff structure debtholders are more interested in the downside risk of their invested capital (Ge et al., 2012). As such debtholders would care more about avoiding adverse events affecting the borrowing firm's interest paying ability, e.g. product failure (Chen et al., 2019). Activities aimed at increasing employee satisfaction, on the one hand, consume valuable resources that could be used elsewhere to help generate profits, leading to reduced interest paying ability and distress costs – which might be viewed unfavorably by debtholders. On the other hand, employee satisfaction activities can reduce the risk of adverse events, e.g., product failure, labor strife, litigation, and increase productivity, motivation and ultimately operating cash flow.

As debtholders are more sensitive to the downside risk, and despite that the literature on firms' employee treatment points to a beneficial link to operating performance, it is not clear how public bondholders view the trade-off between the costs and benefits of employee treatment. This trade-off is better studied within a traded market setting, such as the public bond market, because it would be more instantaneously reflected in bond prices, allowing for more timely inferences compared to the private debt market which tends to react slower.

3.1.7. Asymmetric information theory

Although many similarities exist between the public and private financing setting, it is important to shed light on one significant difference, namely their access to information about the firms' financial capability and future projected growth. While banks and creditors have access to some private information about the borrowers, bondholders do not, resulting in higher information costs for public debt (Fama, 1985). Due to poorer information availability (Fama, 1985), and because the public bond market is less efficiently monitored (Diamond, 1984), the information gap should be even more distinct in the case of public debt financing.

The information gap described can also be referred to as information asymmetry, which occurs in a situation where one party in a transaction is in possession of more information than the other party (Stiglitz, 2002). The type of problem arising as a result of information asymmetry is referred to as agency problems (Eisenhardt, 1989). The situation includes an agent, in this case the issuer, and the principal, the bondholder, where the bondholder lacks information about the issuer's intentions, collateral and assiduousness (Leland & Pyle, 1977). If the two parties have different objectives or risk preferences, the issuer may have an incentive to exploit its knowledge advantage at the expense of the bondholders. As a result of this, companies looking to raise funds commonly face a problem known as the lemon problem (Healy & Palepu, 2001). Although the issuer itself knows the quality of their own projects, the bond investors do not have the ability to distinguish among bad and good firms. The uncertainty experienced by outside investors therefore causes them to demand a risk premium.

If a firm can reduce the information asymmetry, the information risk decreases, which in turn should translate into lower financing costs. To enable financing in this setting, it should therefore be of utmost importance for issuers to address the information gap, which can be done by transferring information between the parties (Eisenhardt, 1989).

3.1.8. Signaling theory

One stream of research, which is applicable in decision-making processes where significant information asymmetries exist, is signaling theory (Francis et al., 2019). For firms and projects of good quality to be financed, a transfer of information must occur from the informed party, to the uninformed (Leland & Pyle, 1977). This may be done by the informed party taking actions to reveal private information, which is then used by the uninformed party as a signal to make inferences about the information that is not directly observable to them (Francis et al., 2019). For the uninformed party to perceive a signal as valid, it must satisfy two conditions. First, it must be observable in advance, and second, the signal must incur significant costs for the signaler (Harrison & Bosse, 2013).

Employee satisfaction could form a valid signal because it is costly for the signaler and can be observed in advance. However, this relies on the assumption that the bondholder perceives a link between employee satisfaction and financial capability in the sense that it conveys information about the firm's future cash flows and valuations and risk.

3.1.9. Screening theory

Screening theory takes another perspective on information asymmetry, which differs from signaling theory in that it focuses on the actions taken by the uninformed party, rather than the actions taken by the informed party. Thus, screening theory is focused on filtering approaches adopted by the uninformed parties to sort firms based on unobservable differences (Riley, 2001; Stiglitz, 1975, 2000). Because lenders and credit institutions can not directly observe credit risk ex ante, they must rely on observable cues to evaluate the risk (Qian et al., 2021).

Qian et al (2021) emphasize that employee satisfaction could serve as a cue, not only for the firm's quality, but also for their intent. How firms treat one of their primary stakeholders, with whom they engage constantly, indicates their intent towards other stakeholder groups (Godfrey, 2005). Furthermore, it serves as an indicator for firms' trustworthiness and integrity, whereof trustworthy and benevolent firms are less likely to participate in activities that harm their stakeholders' interests (Qian et al., 2021). As external stakeholders, bondholders could draw on employee satisfaction as an observable cue to infer information about a firm's risk profile and financial capability.

3.1.10. Concluding remarks

To conclude, studies have highlighted that good employee relations are rewarded by private debtholders with a lower cost of borrowing and that there is a negative relationship between high employee satisfaction and cost of debt (Chi & Chen, 2021; Francis et al., 2019; Qian et al., 2021). These studies all survey, mostly, the price of private debt and study the link between banks, and creditors alike. At the same time, previously mentioned studies show the equity market's inability to incorporate intangibles into security prices. In addition to this the information setting in which public debtholders, in contrast to private debtholders, find themselves allow for more information asymmetry. Whether the bond market thus follow the same suit as banks, and creditors alike, and thus incorporates employee satisfaction into debt pricing as a proxy for human capital quality or fail to do so, as the literature has shown the equity markets to do, still remains an open empirical question.

It should, however, be recognized that the mechanism with which the bond market evaluates, and prices risk differs from equity markets (Bai et al., 2019). Despite this both markets should ultimately be occupied with evaluating the cash flow generating ability of the firm (Black & Scholes, 1973; Merton, 1974).

3.2. Hypotheses formulation

As mentioned, previous literature on the pricing of private debt draws upon screening theory, and supports evidence that employee satisfaction is priced by private debtholders (Chi & Chen, 2021; Francis et al., 2019; Qian et al., 2021). However, employee related expenses associated with employee friendly programs may also constrain a firm's investments and weaken its ability to meet its debt obligations. Increased employee satisfaction does not benefit debtholders of firms facing financial constraints or in the case of firms with more profound agency problems (Chen et al, 2019). On the other hand, empirical evidence in the equity market reports that the value of intangibles are not immediately priced by investors (Aboody & Lev, 1998; Edmans, 2011; Lev & Sougiannis, 1996). If markets are efficient, and reflect all available information, the potential future benefits of employee satisfaction should be reflected in higher valuations upon list announcement and thereby limit any abnormal future bond returns. Thus, the following null and alternative hypothesis is developed:

H0: $Abnormal\ return = 0$, Higher employee satisfaction, as demonstrated through the announcement of list inclusion is immediately reflected in bond prices

H1: $Abnormal\ return \neq 0$, Higher employee satisfaction, as demonstrated through the announcement of list inclusion is not immediately reflected in bond prices

We empirically test this hypothesis by investigating the short-horizon reaction, but also the long-run horizon returns and price performance. This to examine if there is any subsequent correction to any initial reaction present on the bond market.

4. Method

The section outlays a description of the methodology applied for this paper, including an introduction to the event study design, the sample selection process, the measurement of abnormal returns for the short and long-term window, and the procedure for testing for significance.

4.1. Event study research design

An event study approach has been applied to assess how the corporate bond market incorporates the value of employee satisfaction. The event study methodology is a way to use financial market data to measure the impact of a specific event on the value of a firm. The economic impact of the event can then be measured by studying the security prices over a short time period (as well as a longer time period), as the effects of the event should be immediately reflected in security prices, given it is value relevant. The main aim of an event study is to compare the returns of securities conditional on the event (realized return) with the returns of the securities would the event not have happened ("normal" return). Any difference should thus be attributed to the event itself, labeled abnormal return.

Although event studies have most commonly been conducted within an equity market setting, event studies have also been conducted on other securities such as bonds, or preferred stock (Bessembinder et al., 2009; Kothari & Warner, 2007). The purpose of event studies is twofold; not only does it aim to test the wealth effects for a firms' claimholders, but it serves as a test of market efficiency.

The general overview of the event study methodology can be explained in four steps (McKinlay 1997):

1) Definition of event window
2) Computation of expected (or normal) returns
3) Estimation of abnormal returns
4) Statistical testing of the significance of abnormal returns

The event window typically extends over one or several days and must include the specific event date. For the purpose of this study, the event window is defined as four days prior, and four days post the event date – which is the list announcement date of the Best Companies to Work for list by Fortune Magazine. Since we study the list announcements 2003-2021, we have 18 event dates (see appendix A.5).

Bonds trade thinly and narrowing the event window would cause serious loss in the number of return observations rendering any inferences from our results ineffective. This increases the possibility of any confounding information being the factor causing abnormal return rather than the event studied, a limitation of this study. This is a balancing act, especially on bond market event studies. The findings of Ederington et al. (2015) on bond market event studies suggests widening the classical $t-1, t+1$ window to $t-3, t+3$. This also increases the power of statistical tests on abnormal returns (Ederington et al., 2015). These considerations influenced the choice for the event window of $t-4, t+4$. However, mainly to maintain a reasonable sample size while also allowing for detection of any information leakage before the event, the effect of the announcement and the immediate trading days surrounding the event date.

For the long-run horizon returns we explore different event windows all starting from the announcement of the list ranging to up to a year.

The second step comprise the computation of abnormal returns, which is required to determine the excess (abnormal) performance over the market (normal) performance. The general formula for detection of any abnormal return for security i in time period t can therefore be defined as follows:

$$AR_{i,t} = R_{i,t} - E(R_{i,t} \mid X_t)$$

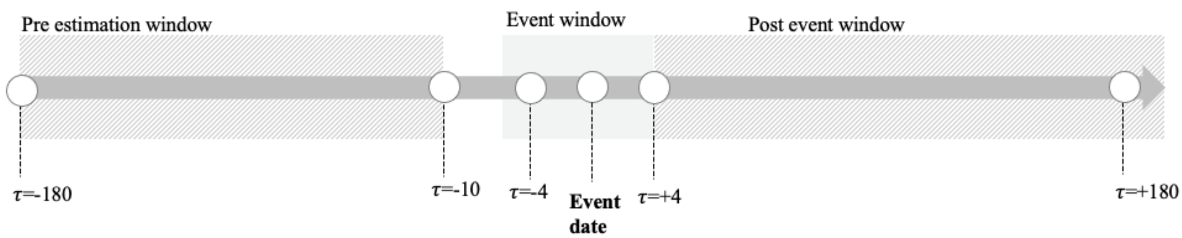
Where

$R_{i,t}$ = the ex-post realized return

$E(R_{i,t} \mid X_t)$ = the expected return conditional on the information X in period t, where t is unrelated to the event.

The above computation for $E(R_{i,t} \mid X_t)$ involves an estimation process where a number of different models have been proposed for determining X_t , e.g. market model, CAPM, Fama-French 3 factor model, matching portfolios, constant return mean model. Which models is superior remains unresolved and no golden standard exists as all models contain advantages and disadvantages (Fama, 1998; Kothari & Warner, 2007). Much of these models rely on estimating returns based on historical information. As such an estimation window must be determined to complete the event study parameters. It is important to avoid overlaps between the estimation window and event window to avoid estimated returns being influenced by the event (e.g., in the case of news leakage). An estimation window of $t_1 = -180$, $t_2 = -10$ was chosen based on previous literature (Bessembinder et al., 2009; Kothari & Warner, 2007).

Figure 1. Illustration of the event study timeline



The measuring of abnormal returns and the estimation models used for calculating expected returns in this study are expanded on further in section 4.3. as well as the statistical testing for significance of abnormal returns in 4.6.

4.2. Sample selection & data collection

We limit our sample to US bonds and firms as the data availability of other markets are limited. Our data can be seen as consisting of three main datasets which is data on employee satisfaction, return data on bonds and data relating to bond attributes. These are merged to comprise our final sample. As the event study methodology entails utilizing the type of event for sample selection, we here first expand on the announcement information on employee satisfaction, the '100 Best Places to Work For' list, then our detailed sample selection and data collection.

Employee satisfaction data – Fortune Magazine's Best Companies to Work For list

The basis for our study is the announcement of the "100 Best Companies to Work for in America" list, which is published annually by Fortune Magazine. The list was first published in a book in 1984 (Levering et al., 1984) and was thereafter updated in 1993 (Levering & Moskowitz, 1993). Since 1998, Fortune Magazine has published it every year, which makes it the oldest publicly available data source on employee satisfaction. The list receives a high level of public attention from the media as well as managers, employees and shareholders (Boustanifar & Kang, 2022; Edmans, 2011), which makes it suitable for the purpose of the study as we aim to study the reaction of information on employee satisfaction. Both Fortune Media Group (the publisher behind Fortune Magazine) and companies on the list issues press releases through their official market communication channels on the announcement day of the list.

Although Fortune publishes the list every year the survey is conducted by the Great Place to Work® Institute[11], and Fortune is thus not participating in the evaluation process of candidates. Otherwise list inclusion could be influenced by clientelism. Firms interested in being included in the list must apply to be considered. This inherent sample selection in using the BC list, as pointed out by Edmans (2011), is reasonable to bias the results downwards or to not impact the results. If there is a correlation between the selection decision and employee satisfaction or the dependent variable, future bond returns, it would have an effect on the results. However, as the firms' own belief regarding their level of employee satisfaction and their belief on whether this information is available to the market affects the application decision and influences the value relevance of the list. Firms with low employee satisfaction would choose to not apply as they would expect to

[11] The Great Place to Work® Institute was founded in 1990, why the list published in 1984 was conducted by Levering and Moskowitz. The four pillars used by the Institute also formed the basis for the evaluation in 1983, with the difference that Levering and Moskowitz surveyed employee directly, rather than through a questionnaire.

not make the list, resulting in more accuracy in identifying high employee satisfaction firms and thus also increase the potential value relevance of the list. On the contrary, if a firm with high employee satisfaction decides to not apply since it believes this does not require independent verification, as the information is already readily available to investors, this would decrease the relative satisfaction level of other firms on the list and diminish the results. Regarding the future bond returns during the event window they are likely to not be correlated to returns at application as the application date and the return window is around 8 months apart. As previous research has showed that private information of insiders are limited to a shorter time period of 100 days (Jenter et al., 2011) the effect should therefore be limited.

All BC candidates are evaluated based on four pillars, including credibility (communication with employees), respect (compensation and opportunities), fairness and pride/camaraderie (celebration, teamwork and philanthropy). The final score allocated to each company consists of two parts. In contrast to many ESG-scores based on written firm policies, two thirds of the score consists of responses to an employee survey developed by the Great Place to Work® Institute. The ability to capture employees' views on their workplace and organizational culture cannot be done by studying written policies, which further supports the choice to use the BC list as an indicator for employee satisfaction. The survey covers a range of topics including job satisfaction, fairness and attitude toward management. The survey is a result of an extensive design process, including, among other things, interviews with employees and workplace experts, researchers, review of academic literature. The survey has been beta-tested in multiple workplaces to ensure that the survey captures the four evaluation pillars. The remaining one third of the score derives from the Institute's evaluation of factors such as culture, pay and benefit programs.

Sample selection

Companies that did not fulfill the below stated criteria have been dropped:

1. All firms included in Fortune Magazine's publication of the BC list since 2003-2021[12]
2. Bond prices must be available for at least the fiscal year end prior to the list publication
3. The company included in the BC-list must be issuer of the bond (i.e. subsidiaries of a BC company have not been included)
4. Companies should not classify as REITs, or other special purpose vehicles

Further filtering requirements for collection of bond data, which are in line with criteria applied by Bai et al., (2019) and Bessembinder et al., (2009).

[12] Ideally a longer sample period would have been preferred in order to increase sample size, however databases providing daily bond prices are only available from July 2002.

5. Bonds issued should be denominated in US dollar
6. The bond should be issued at least six months prior to list inclusion. This in order to minimize any effect from IPO underpricing (this is further controlled for, see section 4.4.4.)
7. Bonds that have a convertible feature, since this distorts the return calculation and makes it impossible to compare the returns of convertible and nonconvertible bonds
8. Bonds that classify as mortgage-backed security, asset backed security, preferred stock, corporate pass-through, foreign currency debenture, yankee bonds, trust preferred capital security or Eurobonds, as these tend to follow the value of the underlaying asset instead of the firm or contain features subjecting the bond to return distortion
9. Bonds that are issued under the Rule 144A, which constitutes an exemption from the registration requirements implied by the Securities Act of 1993

93 unique firms and 5'085 bonds meet these requirements resulting in a total of 405 firm-year observations.

Bond and firm data

Trade Reporting and Compliance Engie (TRACE) constituted the primary source of bond price data for the study. The TRACE database is a part of FINRA (Financial Industry Regulatory Authority), which reports over-the-counter secondary market transactions in eligible fixed income securities. TRACE was first launched in July 2002, why bond data for the BC companies 2003 and onwards have been collected. The price data retrieved from TRACE reflects the clean bond price, and accrued interest must therefore be added to reflect the actual price paid at settlement. Therefore we also require bond specific data for all bonds in our sample in order to calculate accrued interest and so collect coupon payment information, face value, time to maturity along with issue amount, S&P issuer credit rating. If the firm is not rated by S&P we use Moody's or Fitch. This data together with all firm specific control variables were collected from Capital IQ and complemented, if missing, from Refinitiv Eikon. As our sample included private firms' certain data on firm specific control variables had to be manually collected from annual reports of these firms.

With TRACE being a transaction database, where all secondary market transactions are self-reported by market participants to FINRA, it does contain errors, cancellations, corrections and reversals. Therefore we clean the TRACE price data following the recommendations of Bessembinder et al., (2009); Dick-Nielsen, (2009) and by the prevailing instructions of (Dick-Nielsen, 2014). This cleaning means dropping cancelled and reversed as well amending corrected trades. The bond and firm specific data were then merged with TRACE price data to constitute our final sample.

A key characteristic of bonds is that they trade thinly, which also applies to our sample. In order to achieve an acceptable sample and to still maintain a reasonable sample size, both in terms of the study's generalizability and in obtaining a sensible expected return from the models requiring estimating expected returns with historical data, we require that the bonds do not trade in an excessively infrequent manner.[13] Bonds that trade less than three days during the entire event window with at least one day before the event and one day after the event are consequently dropped. We further require bonds to trade at least on 30 days during the estimation window following (Bessembinder et al., 2009), see further in section 4.3.2.

Eliminating these observations leaves a final sample of 905'951 daily trades, 3'433 bonds, 353 firm-year observations and 7c8 unique firms.[14] This compares well with other bond event studies, e.g. those reviewed by Bessembinder et al. (2009, p. 4221).

4.3. Methodological considerations

As mentioned in section 2 the bonds and the bond market possess several unique characteristics which must translate into the research design of this bond market event study. Naturally methodological considerations must be made in order to reliably detect any abnormal returns present during the event. These considerations, outside of the regular event study considerations, include determining the price for the return calculation, handling firms with multiple bonds, considerable cross-sectional heteroskedasticity, the infrequent trading of bonds and accurately capturing risk factors for bonds in the choice of benchmark models. We expand on these considerations in the sections below.

4.3.1. Calculation of daily returns

The bond market is highly illiquid, when comparing to the stock market, and dominated by institutional investors. As bonds trade infrequently it means the number of market participants can for some bonds be limited. Thus determining a market representative price rather than a noisy price representative for an individual investor for the return calculation is inherently difficult. Two approaches were therefore adopted to calculate the daily bond returns. For the first approach, the last price of all trades as reported by TRACE was used. This approach correctly reflects the market conditions at the end of

[13] The issue with infrequent trading is inherent in the bond market and other infrequently traded securities and an issue to be dealt with depending on the purpose and research methodology of the study. This study has primarily dealt with this through using daily price data and balancing the extension of the event window (based on methodological recommendations of Ederington et al. (2015) in order to not lose sample size.

[14] The exact number of trades and bonds vary slightly (3430 compared to 3433) depending on the method of determining each bonds last price for per day. Thus, we obtain two different samples for the two price calculation methods. However, this does not affect the number of event-day observations, number of firm-year observations and unique firm. As stated in section 5.1.2 they yield virtually identical results and only the trade weighted trade ≥100K approach is reported.

the day but can according to Bessembinder et al. (2009) introduce more noise when the last trade of the day is small. This is because since smaller trades in the bond market tend to have larger spreads. Trading costs can vary significantly by trade size, due to the institutional nature of the bond market with the average trade being very large compared to equity market, and because of the illiquidity of the market. Weighting each trade by its size should more accurately reflect the underlying price as seen by the market, as more weight is placed on the institutional trades which incur lower execution costs and smaller spreads (Bessembinder et al. 2009). For the second method, the daily prices were therefore constructed by weighting each trade by its size in line with the approach by Bessembinder et al., (2009). In line with Edwards et al. (2007) and Bessembinder et al. (2009), all trades under $100’000 were also eliminated, as these tend to represent the non-institutional trades. Note however that the number of trades that are dropped due to this consideration is very low.

Bond returns are then calculated as displayed below:

$$R_{i,t} = \frac{((DP_{i,t} - DP_{i,t-1}) + C_{i,t})}{P_{i,t-1}}$$

Where

$R_{i,t}$ = the return of bond i , between the closing of day $t-1$ to closing of day t

$DP_t =$ the dirty price of the bond at day t

$DP_{t-1} =$ the dirty price of the bond at day $t-1$

$C_{i,t}$ = coupon payment, if any, paid to holders of bond i

The dirty price is calculated as follows:

$$R_{i,t} = \frac{((P_{i,t} - P_{i,t-1}) + AI_{i,t})}{P_{i,t-1}}$$

Where

P_t = the clean or quoted price of bond i at day t,

P_{t-1} = the clean or quoted price of bond i at day $t-1$

$AI_{i,t}$ = the interest accrued to bond i at day $t-1$ which is calculated as follows:

$$Accrued\ interest = \frac{\left(\frac{Coupon\ rate \cdot Face\ Value}{Payment\ Frequency}\right)}{Days\ in\ payment\ period} \times Days\ until\ next\ coupon$$

The returns have been winsorized at the 1% and 99% level for both of the price calculation methods to prevent outliers influencing the results. Using two methods for calculating the return essentially translates into using two different samples.

4.3.2. Benchmark models for estimating expected returns

Any research conducted on abnormal returns contains a critical assumption regarding the model used to estimate expected returns, namely that the chosen model is the true model which does not fail to incorporate any important risk factors. As noted by Fama (1998) an event study is therefore fundamentally a joint test of market inefficiency and a model for estimating expected returns. As the true or appropriate model for estimating expected returns still remains unresolved Boustanifar & Kang, (2022) highlight the importance of using several alternative models. As this study is concerned with the bond market the estimation models have been chosen to reflect the risk factors common to bonds. Following the important work of Bessembinder et al., (2009) on bond event study methodology we use four different models to estimate the expected returns. These are the mean-adjusted model, a factor model and two matching portfolio models, which we expand on below.

Mean-adjusted model

The most popular method, according to Bessembinder et al., (2009), for estimating abnormal returns have been the mean-adjusted model which was initially introduced by Handjinicolaou & Kalay (1984). The mean-adjusted model involves using the mean of historical returns and adjusting for the term structure of interest rates. What is called the premium return (PR) is calculated by taking the historical return on the bond less the return on a matched treasury security (TR) with the most similar maturity and coupon (Handjinicolaou & Kalay, 1984), as defined below:

$$PR_{i,t} = BR_{i,t} - TR_{i,t}$$

The expected return is defined as the average (PR) over the previous y periods, a prespecified estimation period, as defined below:

$$E(R_{i,t}) = \left(\sum_{t=-1}^{-y} PR_{i,t}\right)\frac{1}{y}$$

A period of 180 days was used for the estimation of the expected return. The abnormal return (AR) for bond i is then calculated as the excess of the premium return (PR) over the expected return (ER):

$$AR_{i,t} = PR_{i,t} - E(R_{i,t})$$

Handjinicolaou & Kalay (1984) study a smaller sample and over a shorter time period. As our sample is larger and spans a longer time period, compared to Handjinicolaou & Kalay (1984) and other bond event studies, the matching optimization becomes more difficult. This is because the maturity and coupon variation increase with sample size and period studied as well as the inevitable fact that the number of available treasury securities for an acceptable maturity and coupon range is limited. For the purpose of optimizing the matching based on our unique sample, daily data for 18 different total return treasury indices with different maturities were collected.[15] Each bond included in the sample was then matched with a treasury index based on its time to maturity.

The mean-adjusted model relies on the assumption that the bond premium relative to the matched treasury security is constant over time, an assumption that does not necessarily hold. However, the assumption is more likely to be accurate for short time periods, which is why previous studies tend to use a short estimation window (e.g. $t-60, t-16$) (Bessembinder et al., 2009). A drawback of this is an inherently noisier estimation period, additionally Bessembinder et al. (2009) finds that increasing the estimation period to 180 days results in fewer type II errors. As such we adopt an estimation period of $t-10, t-180$ days where t is the event day. We further require that the bonds trade at least 30 days during the estimation period, in order to maintain robustness in the estimation.

Multifactor models

In a seminal paper Fama & French (1993) developed a multifactor model for predicting bond returns extending on the famous capital asset pricing model (CAPM). The model consists of three equity factors, the market risk premium ($RMRF$), the small-minus-big factor (SMB) and the high-minus-low factor (HLM) and two common bond-specific risk factors which are related to maturity ($TERM$) and the default risk (DEF). This five-factor bond model is used by Bessembinder et al. (2009). However based on previous research on momentum (which is a common factor deployed in equity factor models) has been found to explain bond returns (Jostova et al., 2013). Thus we complement our factor model with the Carhart (1997) equity momentum factor (MOM), used in more recent literature on bond market factor models (Houweling & van Zundert, 2017) as a second method for estimating the expected returns:

$$R_{i,t} - R_{f,} = \alpha + \beta_1 RMRF_{i,t} + \beta_2 SMB_{i,t} + \beta_3 HML_{i,t} + \beta_4 MOM_{i,t} + \beta_5 TERM_{i,t} + \beta_6 DEF_{i,t} + \varepsilon_{i,t}$$

[15] ICE Bank of America US treasury indices were chosen due to its historical data availability as well as having the most time to maturity categories.

Where R_t is the daily return for bond i, R_{ft} is the risk-free rate, $RMRF$ is the equity market premium, SMB is the equity size premium, HLM is the equity value premium, MOM is the equity momentum premium, the $TERM$ is the default-free interest rate term premium and is meant to proxy for the unexpected changes in interest rates. It is defined as the difference between the return of long-term government bonds and the return on short-term treasury bills (Fama & French, 1993). The other risk factor for bonds DEF, i.e. the corporate bond market premium, represents bonds' shift in probability of default. This is defined as the excess return of a portfolio of long-term corporate bonds over the return of long-term government bonds (Fama & French, 1993). The four equity factors $(RMRF, SMB, HLM, MOM)$ were obtained from Kenneth French's website.[16] We have constructed the default and term factors in a similar way as Houweling & van Zundert (2017). The $TERM$ is constructed using the IHS Markit iBoxx 7-10 year treasury total return index and the treasury bill rate obtained from Kenneth French website. For the DEF factor the IHS Markit iBoxx US Corporate Bonds total return index was chosen as a proxy for the corporate bond portfolio and the IHS Markit iBoxx 7-10 year treasury total return index as a proxy for long-term government bonds.[17]

An estimation window of $t-10, t-180$ days where t is the event day was chosen for the regression used to estimate the abnormal returns with the multi-factor model specified above, following previous literature (Kothari & Warner, 2007). At least 30 trades are required during the estimation period in order to maintain robustness in the estimation. In the regression model above the constant is the daily abnormal return for each bond.

Matching portfolio models

Another common model to estimate expected returns is using matching portfolios based on common risk factors. Relating to bonds these are default risk and time-to-maturity risk (Bessembinder et al., 2009). Both Kim & McConnell (1977) and Bessembinder et al. (2009) use matching portfolios. Bessembinder et al. (2009) consider both a size and liquidity factor as well but do not find them effective. A number of reference portfolios have therefore also been constructed to control for risk with different methods. Matching portfolios were constructed based on bond rating and time to maturity, where daily total return data for 21 indices was collected. The indices collected are Bank of America's ICE indices, which are segmented based on time to maturity and bond rating. Following Bessembinder et al. (2009) the bond rating categories are based on the S&P credit rating scale, and spans from AAA to CCC, and are divided into three time to maturity categories: 1-5 years, 5-10 years, 10+ years.

The long-term issuer credit rating at the time of list inclusion was collected for all the BC companies, and thereafter converted to a numerical scale in accordance with the

[16] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[17] All indices were chosen due to data availability and for historical index data being available during the entire time period studied.

frequently used schedule: CCC+ = 1 B3/B- = 2, B2/B = 3, and so on through Aaa/AAA = 17. We consider the firm-level credit rating rather than debt issue ratings because the former reflects the overall credit risk of the company, while the latter reflect the default risk associated with a single bond (Weber, 2006), and thus, are less likely to be influenced by stakeholder activities (Attig et al., 2013). Based on the rating and time to maturity category, every BC company could be assigned with a benchmark portfolio.

To ensure that abnormal return is not merely driven by BC companies being in an industry that seems to experience higher returns we control for this by constructing additional matching portfolios based on industry. Each BC company was assigned to a category based on its two-digit SIC code, and time to maturity (1-5 years, 5-10 years, 10+ years). Based on this, IHS Markit iBoxx indices were collected for 17 different two-digit SIC codes, and three different time to maturity categories, resulting in a total of 52 indices.[18] A finer partitioning according to the frequently used Fama-French 49 industry classification was not possible due to the availability of industry specific indices. The method chosen for defining industries intended to maximize the partitioning of industries but at the same time maintain feasibility.

We use these matched portfolios as the expected return for the bonds in the sample. The abnormal return for each bond i at time t is calculated accordingly as:

$$AR_{i,t} = R_{i,t} - E(R_{i.t})$$

Where

$R_{i,t}$ = the realized return for bond i at day t

$E(R_{i,t})$ = the return of bond i's matched portfolio at day t, i.e. the expected return

4.3.3. Firm-level bond returns

It is not uncommon for firms to have multiple bonds outstanding, with different time to maturity, coupon and other attributes each individually affecting their pricing. This leaves three options in terms of sampling: (i) choosing a representative bond for each firm in the sample, (ii) consider each bond a separate observation or (iii) treat the firm as a portfolio consisting of each bond issued by the firm. As this study is concerned with a firm specific event and aims to study the change in value associated with the list announcement the latter approach was chosen.[19] Additionally the first approach is prone to considerable selection biases in choosing the representative bond, which might misrepresent any firm-

[18] Once again, the IHS Markit iBoxx indices were used due to data availability and for historical index data being available during the entire time period studied.

[19] When selecting multiple observations for each firm any model misspecification would be mitigated through the aggregation of returns, generating more robust results (Bessembinder et al., 2009).

level effects. Certain events could affect bonds differently depending on the attributes of the bond (coupon, maturity, etc.). The second approach suffers from a violation of sample observations being independent for bonds issued by the same firm, leading to an inflation of the t-statistic or higher probability of type I errors (Bessembinder et al., 2009). These selection biases would also be amplified as the majority of the BC companies in our sample have multiple bonds outstanding.

A firm-level portfolio was accordingly formed where the abnormal return for each bond is weighted with its amount outstanding at day t. The weighted average abnormal bond return for each firm is then calculated as follows:

$$AR_f = \sum_{i=1}^{J} AR_i \, w_{i,t}$$

j represents the total number of bonds outstanding for each firm and year f, and w corresponds to the market value weight of bond i at time t relative to the total market value of bonds for the firm.

4.4. Measuring abnormal returns | Short horizon

4.4.1. Aggregation of abnormal returns

In order to analyze the short horizon impact of the list announcement in on returns of BCs further aggregation of the returns are needed.

To be able to control if firm specific factors are driving the abnormal returns and to study the multi-period effect of the event a time-series aggregation across the event window for each firm-year observation is needed. We therefore calculate cumulative abnormal return, based on the following:

$$CAR_i(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_{i,t}$$

Where

$AR_{i,t}$ = the abnormal return for firm i at day t

(t_1, t_2) = the event window specification

CAR_i = the sum of abnormal return for firm i across the event window specification

As this study is interested in the impact of a pool of firm and studying the wealth effects of list announcement on debtholders, we make a cross-sectional aggregation of the abnormal returns in the event window. If the focus of the study is to determine if the event is, on average, associated with a change in the wealth of security holders, a mean effects approach is to be preferred (Kothari & Warner, 2007). So, in order to determine the average effect of the list announcement we aggregate average abnormal returns (AAR) per day according to:

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

Where

$AR_{i,t}$ = the abnormal return for firm i at day t

AAR_t = the average abnormal return at day t across the entire population

N = the number of firms in the population

We calculate this return measure (AAR) for each day in the event window to detect any information leakage or sign of investor anticipation of the event. This aggregation also helps eliminate any idiosyncrasies in certain firms' returns.

Thereafter, aggregation is made across time, in order to understand and illustrate the average effect across the entire event window to arrive at the cumulative average abnormal return ($CAAR$):

$$CAAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AAR_t$$

Where

AAR_t = the average abnormal return at day t across the entire population

(t_1, t_2) = the event window specification.

4.4.2. Standardization of abnormal returns

The common factor of the sample firms is their inclusion in the BC-list. Hence, for each BC list year, all firms' securities are affected by the same market information at the same time. Having the same event date for many firms imply that bond prices violate the assumption of being independent, which causes cross-correlation and downward biased standard errors, which in turn would lead to over-rejection of the null hypothesis (Kolari & Pynnönen, 2010). During these circumstances when cross-correlation is present, the preferred approach is to use standardized abnormal returns[20] (Ederington et al., 2015; Kolari & Pynnönen, 2010). Standardized abnormal returns are obtained by dividing abnormal returns with the standard deviation of abnormal returns.

Using standardized returns rather than unstandardized returns also helps to reduce the heteroskedasticity issue in returns (Ederington et al., 2015). The issue with heteroskedasticity in studying returns is a well-known and inherent issue which too is present in research of equity returns. However, the issue is considerably amplified in bond returns, as reported by both Ederington et al. (2015) Bessembinder et al. (2009). Brown & Warner, (1985) find that statistical tests based on standardized returns have higher power, however according to Kothari & Warner (2007) it makes little difference in short-horizon event studies (referring mainly to the equity markets). Ederington et al. (2015) develop methodologies specifically applicable to the bond market. They find that for bonds the heteroskedasticity issue is serious and recommends using standardized returns. We thus follow the econometrical recommendations of Ederington et al. (2015) and calculate the standard deviation of the abnormal returns over the $t-55, t-6$ and $t+6, t+55$ periods where t is the event day and where abnormal return is calculated as described above. The aggregated abnormal return measures above (CAR, AAR and CAAR) are aggregated in the same manner as above but use the standardized abnormal returns as a base instead.[21]

Kolari & Pynnönen (2010) remark that standardized returns lack any relevant economical interpretation and should be used only for statistical testing while interpretation should be made using “raw” unstandardized returns. Standardized returns are therefore deployed in testing the significance of abnormal returns and raw abnormal returns to interpret the magnitude and economic significance of the short horizon impact from the list announcement.

4.4.3. Regression models

To determine the relationship between abnormal returns and the list announcement a multivariate regression is used. A general ordinary least-square multivariate regression equation takes the following form where y is the outcome variable a is the constant, x is the explanatory variable with its corresponding coefficient β and ε is the unobserved error term:

$$y_{i,t} = a + \beta_1 x_{1,it} + \cdots + \beta_k x_{k,it} + \varepsilon_{i,t}$$

[20] Also commonly referred to scaled returns or scaled residuals.
[21] These standardized return measures are denoted SCAR, SAAR and SCAAR.

Any ordinary least-square (OLS) regression assumes a number of model assumptions. OLS regressions require no autocorrelation, i.e. the error terms are uncorrelated, homoscedasticity, i.e. constant variance in the error term, uncorrelation between the error term and explanatory variables, no multicollinearity, i.e. independence of explanatory variables and normally distributed error terms (Brooks, 2014). Depending on the sample characteristics the econometrical model needs to be adjusted to accommodate for any violations. See appendix for further testing of model assumptions, as we here address considerations made for any serious violations.

It is common for several of the sample firms to reappear on the list across a number of years which causes autocorrelation in the independent variables. To compensate for this we cluster our standard errors based on firm. Another issue when conducting an event study is that the aggregation of abnormal returns assumes that the event window for the firms do not have any overlap. This assumption allows for the calculation of the variance of the aggregated sample cumulative abnormal returns and not having to consider the covariance between firms (MacKinlay, 1997). If there is overlap amongst the firm's event window, i.e. event-day clustering, the assumption no longer holds rendering results inappropriate to draw inferences from. MacKinlay (1997) offers guidance on this issue and suggests using a multivariate model with a dummy variable for each event date. Hence, we adjust our regression by using this approach.[22] This type of fixed effects regression is also well suited to reduce endogeneity concerns in our model, as any omitted variable are likely to correlate with many of our firm specific control variables.

Given that the event window spans across multiple days, and to allow for firm specific controlling, the time-series cumulative measure of abnormal return (CAR) for each firm-year observation is used as the dependent variable. The cross-section of abnormal return for each day in the event window is also regressed in the same manner.

Table 1. Overview of control variables

Control variables	**Definition**	**Expected sign**
Bond-level controls		
COV	Dummy that that takes that value of one if that bond has any covenants, otherwise zero	+
IPO	Dummy variable that takes the value of one if the bond has been issued six months before, but less than one year prior to list inclusion, otherwise zero	+

[22] More specifically we use a year fixed effects regression using the reghdfe command in STATA for each year as the event date is year specific.

END_MAT	Dummy that takes the value of one if the bond matures within one year after being included in the list, otherwise zero	-
Firm-level controls		
RAT	Issuer credit rating which has been converted into a numeric range, spanning from 1 (=CCC+) to 17 (=AAA)	+
SIZE	Log of total revenues of the issuer	-
LEV	Liabilities divided by the total value of assets for the fiscal year before publication	+
ROA	Income before extraordinary items divided by total assets	-
INT_COV	Operating income before depreciation divided by total assets	+
LOSS	Dummy that takes the value one if the net income before extraordinary items is negative for the current and prior year, and otherwise takes the value zero	+
INTANG	The value of intangible assets divided by the value of total assets	-
NIG	A dummy variable which takes the value of one if the firm has an issuer credit rating lower than BBB- (commonly referred to as non-investment grade), otherwise zero	+
List-level controls		
FIRST	A dummy variable which takes the value of one if the firm is on the BC list for the first time, and otherwise takes the value zero	+
RANK	Specifies the list ranking of the firm for the BC list year. Hence takes a value from 1-100	+
TOP25	A dummy variable which takes the value of one if the firm is one of the top 25 firms on the list, otherwise takes the value of zero	+
BOT25	A dummy variable which takes the value of one if the firm is one of the bottom 25 firms on the list, otherwise takes the value of zero	-

Note: The control variables are all measured at the end of the fiscal year prior to list inclusion.

4.4.4. Control variables

When companies issue bonds, the pricing of the bonds will be affected by several factors other than the information on employee satisfaction, why these factors should be controlled for.

Previous research on the incorporation of information on employee satisfaction by bondholders have identified two categories of control variables: bond-level controls, and firm-level controls (E.g., Chen et al. (2019), Bauer et al. (2009). We also introduce list-level controls in order to identify if any particular segment of firms on the list are the contributing factor to any abnormal returns. An overview of the control variables used, and respective definitions can be found in table 1, whereas their connection to the literature and motivation is further expanded on below.

Firm-level controls

With regards to firm-level controls, we take into account characteristics of the BC companies that are commonly controlled for in the literature on bonds and event studies (see e.g. Bauer et al., (2009); Chen et al., (2019); Edmans, (2011)). We therefore include the following control variables in our regressions: issuer size, leverage, return on assets, interest coverage, loss, intangibles ratio. Issuer size is controlled for due to two reasons. Firstly being that larger firms are less likely to default, causing their returns to be lower, thus we expect it to be negative. Secondly larger firms tend to issue the largest bonds which in turn tend to be the most liquid bonds (Bessembinder et al., 2009). As illiquidity is a key characteristic of the bond market which demands a premium from investors, we also use size as a proxy to control for this.

Firms with higher leverage are closer to default in addition to a higher expected absolute loss for debtholders, causing investors to demand higher risk premiums. Verwijmeren & Derwall (2010) also report evidence that employee satisfaction has a negative relation to leverage. So, in order to ensure leverage is not influencing abnormal returns we thus control for this factor and based on above reasoning we expect it to be positively related.

A higher return on assets indicates that a firm is more profitable and therefore have a lower probability of default, causing returns to be lower. As with size, we thus include it among the control variables and expect it to have a negative relationship.

One of the primary objectives of a credit screening is assessing whether the borrower is solvent enough to pay its debt obligations. Firms with a lower ability to repay, ceteris paribus, should demand a higher return from investors, which is why we include interest coverage and expect to find a positive relation. Likewise, to further control for firms that are making a loss, indicating a deteriorating ability to repay, we construct a dummy variable taking the value of one if firms have a negative net income.

The credit quality of the issuer captures information of its default probability and loss severity. Bai et al. (2019) finds that credit risk, proxied by credit ratings, predicts the cross-sectional variation in future bond returns, thus any abnormal return could be driven by credit quality factors. We already control for this using other methods but for conservative measures we include a control variable where a larger number indicates lower credit risk or higher credit quality. As issuers with lower ratings are more likely to enter into default and therefore demand higher returns, we expect this to be positively related to returns. We use an alternative measure of credit quality by introducing a dummy if the firm is a non-investment grade firm (NIG)[23], as the characteristics between NIG-bonds and IG-bonds vary greatly – most importantly price variance (Ederington et al., 2015).

Findings of (Francis et al., 2019) show that firms committed to fair employee treatment policies benefit from lower loan prices, and in particular this effect is stronger for firms with high levels of intangibles assets. To control for if firms with high levels of intangibles are accounting for any abnormal returns we include a control for this.

Since our sample includes both private firms and publicly listed firms, we refrain from using any market-based control variables, as it would limit the sample size.

Bond level controls

Underpricing has been identified as an anomaly in both equity markets (e.g. Ritter, 1991) and in the bond market (Cai et al., 2007). We require bonds to be issued at least six months before list announcement to be included in the sample, however underpricing has been found to persist over longer periods (Loughran, 1993; Ritter, 1991). Therefore, a control variable in the form of a dummy addressing this is constructed. By doing so, we can control for the bond IPOs not driving the abnormal returns. The same is true for the bonds that matures within a year of being included in the list. All major corporate bond indices tend to delist bonds that mature within a year, which could potentially distort the return calculation for those bonds as index-tracking investors change their holdings (Bai et al., 2019). Thus, a control for this is used. Covenants are contractual obligations imposed on the issuer to limit certain actions and protect the bondholder. Covenants are therefore an indirect indicator of cost of debt (Ge & Liu, 2015) and an individual risk factor that influences the price of a bond. Francis et al. (2019) finds evidence for fair employee treatment limiting the use of covenants. To further control for this we construct a dummy variable if the bond has any covenants.

As all analysis and statistical testing for any abnormal returns are made at the firm-level, after aggregation of the bond level abnormal returns, all bond-level control variables are converted from dummies to represent a percentage of the sample firm's bonds outstanding which observe these characteristics.

List-level controls

By introducing control variables specific to this study, we hope to shed light on if different factors relating to a firms' inclusion on the list is driving any abnormal return. By controlling for these factors we can draw inferences on whether it is the list inclusion itself driving the results, or other ranking attributes.

[23] As none of the issuer credit rating differed from bond credit rating, we use NIG and IG firms and NIG and IG bonds interchangeably. Non-investment grade is often referred to as speculative grade or "junk bonds".

Edmans (2011) indicates that the previously found abnormal returns on the equity market could be due to a mispricing of intangibles (for a more complete explanation, see section 3.1.2) and also reports that such a correction takes place over the longer run. Under that "mispricing story" the abnormal returns for a firm would be the greatest when it is first included on the list. New firms on the list could therefore disproportionately drive the abnormal returns and we therefore control for this by constructing a dummy variable if it is the first time the firm appears on the list.

Another attribute of the list itself is the ranking from 1-100 which poses the question of the marginal effect of the ranking on the list, as the number one ranked firm should have a higher employee satisfaction, it could result in driving abnormal returns more than a 100 ranked firm. The marginal effect on returns of being ranked one position lower than another firm in ranking is likely to be low. However, much focus is put on firms in the top on the list. In order to control for any such effect of list ranking position we use firms' ranking on the list as a control variable and construct two dummy variables, one for top and one for bottom ranked firms.

4.5. Measuring abnormal returns | Long-run horizon

The measuring of abnormal returns for longer event horizons differs from that of shorter event horizons. This mainly in the different aggregation of security-specific abnormal returns and adjustment of statistical significance of abnormal returns. We touch on these considerations below.

4.5.1. Buy-and-hold abnormal returns

Investigating the long-run horizon returns, also sometimes referred to as drift, of BCs after list inclusion involves calculating the return from investing in a portfolio of all bonds issued by firms included on the list at announcement and selling at a prespecified holding period T. This return is then compared with the return to a portfolio of matched bonds based on certain characteristics (matched benchmark portfolio) (Kothari & Warner, 2007). Known as the Buy-and-Hold Abnormal Return (BHAR), it better replicates investors' actual investment action and has been argued to be more accurate for statistical reasons (Conrad & Kaul, 1993), as compared to the Cumulative Abnormal Return (CAR) approach. Returns are geometrically compounded on a periodic basis (we use daily) up until the end of holding period T as below:

$$BHAR_i(t-T) = \prod_{t=1}^{\tau}\left[1+R_{i,t}\right] - \prod_{t=1}^{\tau}\left[1+E(R_{i,t})\right]$$

where $E(R_{it})$ is the return on either the matched bond to the event bond i, or it is the return on a matched benchmark portfolio. We examine $T = 30, 60, 90 \dots 360$ days after the announcement of the list to detect any corrections related to the announcement of the list, and if so when these happen.

For examining the long-run horizon returns we use the two matching portfolios based on industry and rating as benchmark portfolios as the two other models do not present any matching characteristics (see further details in section 4.3.2.). One option is constructing a matched portfolio where bonds issued by firms displaying similar characteristics as the bond issued by the BCs using the factors in the multifactor models of Carhart (1997) or Fama & French (1993) as matching characteristics. However, due to the cumbersome work of manually constructing bond portfolios and the time constraints of this study the matching portfolios on industry and rating was considered to be a sufficient benchmark.

We also investigate if there is any long-run abnormal performance to a trading strategy by holding an equal-weight portfolio of bonds issued by BCs, denoted 'The BC portfolio'. This is done by calculating the abnormal return over the matched benchmark portfolios to holding 'The BC portfolio' with yearly rebalancing during the sample period (2003-2021). The portfolio is rebalanced when a new list is announced and uses the same calculation method as the BHAR approach above.

4.5.2. Adjusting for cross-correlation

Assessing statistical significance for long-run horizon event studies and using the BHAR approach has been proved to be difficult primarily due to the cross-correlation in returns between event firms (Kothari & Warner, 2007; Mitchell & Stafford, 2000). This violates the assumed independence required for a standard t-test leading to a downward bias in estimating the standard deviation and over-rejection of the null hypothesis of no effect (Mitchell & Stafford, 2000). This bias can be of a large magnitude and increases with sample size and cross-correlation in the sample. It is therefore crucial to adjust for this bias to draw rigorous inferences in long-run horizon event studies (Kothari & Warner, 2007). We therefore adjust according to Mitchell & Stafford's (2000) recommendations:

$$\sigma_{AR} = \left[\frac{1}{N}\sigma^2 + \frac{N-1}{N}\rho_{i,j}\sigma^2\right]^{1/2}$$

where N is the number of sample firms, σ^2 is the variance of abnormal returns, which is assumed to be the same for all firms and $\rho_{i,j}$ is the correlation between firm i and j 's abnormal returns.

4.6. Testing for significance in abnormal returns

To test for significance of any abnormal returns in we run both parametric and nonparametric tests. For the parametric test we use a Patell (1976) test adjusted for the bond market, based on Ederington et al.'s (2015) methods, to determine whether the mean abnormal return was significantly different from zero. In other words, if higher employee satisfaction, as indicated by the list inclusion, is immediately reflected in bond prices. The following test statistic was therefore calculated: [24]

$$t_{AAR} = \sqrt{N}\frac{SAAR_t}{\sigma_{AR}}$$

Where

$$\sigma_{SAR}\frac{1}{N-1}\sum_{i}^{N}(SAR_{i,t} - SAAR_t)^2$$

$SAAR =$ the standardized average abnormal return (for further explanation on this see section 4.4.2.)

$N =$ the number of observations (number of firms when calculating $SAAR$ and number of days in the event window when calculating $SCAAR$)

Estimating σ_{SAR} is either based on the cross-sectional standard deviation of the abnormal return or based on a time-series standard deviation of each firm i (Ederington et al., 2015). As we use standardized abnormal returns (SAR), for the short horizon, where the time-series standard deviation for each firm is used to adjust the abnormal returns, using a cross-sectional standard deviation is more sensible. The benefit of estimating a cross-sectional standard deviation is that it allows the event itself to impact the volatility (Ederington et al., 2015).

We use the same calculation when examining the long-run horizon significance but adjust for the bias in the standard deviation that arises in long-run horizon event studies due to cross-correlation (see section 4.5.2.). Standardized returns are not used in the long-run horizon as the adjustment mentioned in 4.5.2. deals with this issue in long-run event studies better.

Bessembinder et al. (2009) show that the t-test is not well suited for studies on bond returns due to their negative skewness and leads to disproportionate type I errors. They argue for using nonparametric tests to draw inferences on bond returns but conclude that it is essential to consider both types of tests in bond event studies. Hence a nonparametric Wilcoxon signed-rank test was also employed for further robustness in drawing any inferences.

[24] We use the same formula for calculating a test statistic for SCAAR and BHAR.

5. **Descriptive statistics**

The following section aims to provide an overview of the data on which the tests and following analysis is conducted. The section starts with summary statistics to provide nuance on the sample composition based on characteristics such as size, rating and industry, and is then followed by a correlation matrix.

5.1. Summary statistics

Our sample consists of 353 firm-year observations on the announcement of the ‘100 Best Companies to Work For’ list on 78 firms (specified in the appendix) over the time period 2003-2021. Table 2 presents descriptive statistics of our sample and relevant control variables.

As noted in Boustanifar & Kang, (2022) and Edmans, (2011) BCs are larger firms, with a mean (median) sales of $23.4bn ($13.29bn) and a mean (median) market cap of $62.89bn ($32.64bn). BCs display relatively high book-to-market ratios and have relatively large amounts of intangibles on their balance sheet, 19.39% of total assets. BCs are also notably of a high creditworthiness, and tend to be investment grade, 60% of the sample, while 40% of BCs are non-investment grade firms. This is also noticeable in the mean credit rating of A-.

Table 2. Descriptive statistics for sample. Panel A displays summary characteristics of the BCs, panel B summary characteristics of bonds issued by BCs and panel C summary characteristics of the sample's daily abnormal returns.

	N	**Mean**	**Median**	**Std.**	**Min**	**Max**	**P25**	**P75**
A. *descriptive statistics on BCs*								
Sales ($bn)	353	23.4	13.29	24.90	0.512	163.77	7.33	33.33
Market capitalization ($bn)	341	62.89	32.64	78.68	0.476	539.7	14.82	81.43
Return on assets (%)	353	0.0661	0.0679	0.0471	-0.0993	0.2160	0.0251	0.0973
Book-to-market (%)	340	0.3637	0.2870	0.2931	-0.2084	1.6146	0.1727	0.4589
Leverage (%)	353	0.6110	0.5928	0.2430	0.0000	1.5903	0.4617	0.8120
Interest coverage ratio(x)	353	69.79x	1.45x	352.13x	-45.93x	3346.0x	1.45x	1.45x
Intangibles ratio (%)	353	0.1939	0.1399	0.1915	0.0000	0.7704	0.0316	0.2850
Credit Rating	353	10.61 (A-)	11 (A-)	2.72	1 (CCC+)	17 (AAA)	9 (BBB)	13 (A+)
List ranking	353	57	61	28.6	1	100	34	82
B. *descriptive statistics on BCs Bonds*	**N**	**Mean**	**Median**	**Std.**	**Min**	**Max**	**P25**	**P75**
Offering amount ($bn)	3433	8.52	6.00	8.72	0.005	57.45	0.034	12.5
Covenant (dummy)	3433	56.73%	100%	0.4964	0%	100%	0%	100%
End of maturity (dummy)	3433	6.09%	0%	0.2391	0%	100%	0%	0%
IPO (dummy)	3433	9.50%	0%	0.2932	0%	100%	0%	0%
C. *descriptive daily abnormal return*	**N**	**Mean**	**Median**	**Std.**	**Min**	**Max**	**P25**	**P75**
Abnormal return MAM (%)	115 988	0.02	0.03	0.72	-7.63	6.87	-0.18	0.27
Abnormal return MFM (%)	116 733	0.15	0.15	0.38	-10.84	15.17	-0.02	0.30
Abnormal return MPI (%)	116 362	0.17	0.18	0.77	-8.05	5.36	-0.07	0.47
Abnormal return MPR (%)	116 324	0.18	0.19	0.78	-8.24	5.72	-0.08	0.49

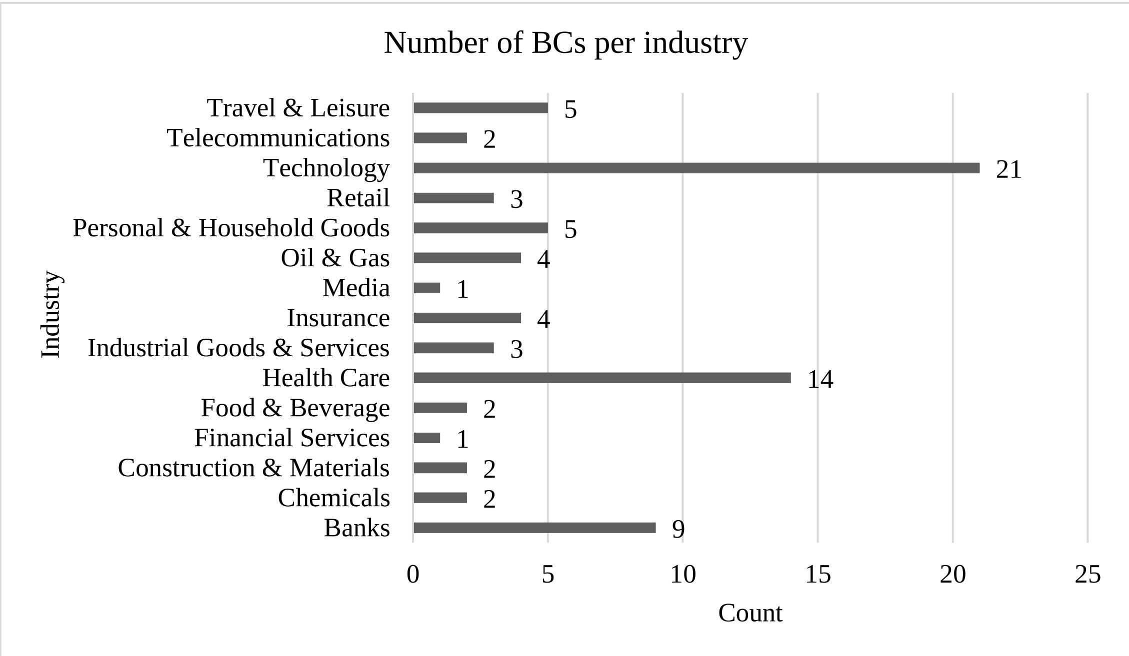
Note: Daily abnormal returns are displayed in basis points (bps), 1 basis point equals 1/100 of a percent. The mean-adjusted model is denoted MAM, the multifactor model is denoted MFM and the two matching portfolios MPI for industry matched and MPR for rating matched.

The BCs tend to also issue large bonds with a mean (median) offering amount of $8.52bn ($6bn). There is also a noticeable variation in the size of each bond given the smallest bond is $5m and the largest bond is $57.45bn. Coupled with the higher credit worthiness, bonds issued by BCs experience fewer debt restrictions in the form of covenants. Few of the bonds in the sample are issued in close proximity to the list announcement and thus the event window. Similarly few bonds mature within one year of list announcement

For the daily abnormal returns the mean and median returns vary slightly across the different models with the returns estimated with the mean-adjusted model (MAM) displaying the most significant difference, 2 bps (0.002%) compared to 15 bps (0.0015%), 17 bps (0.0017%) and 18 bps (0.0017%) for the other models. This variation in returns between the returns for each model is noticeable for the MFM and could be due to differing model specifications.

The industries in our sample of BCs can be seen in figure 2, where technology (21), health care (14) and banks (9) are the most common industries. Knowledge, and human resource, intense industries (e.g. technology, health care, banks) seem to be overrepresented in the sample. This is reasonable given the importance of employee satisfaction for maintaining quality of those assets. Overall the industry distribution is representative for the general industry composition in the US.

Figure 2. Overview of industry composition in the sample



The distribution of credit ratings in the sample is presented in table 3 and is skewed towards more investment grade firms and bonds. Highlighting the importance to further control for this characteristic.

Table 3. Overview of rating composition in the sample, on both firm-level and bond-level

Credit rating category	Firms per rating category	%	Bonds per rating category	%
AAA	4	1,13%	18	0,52%
AA+	9	2,55%	55	1,60%
AA	5	1,42%	18	0,52%
AA-	21	5,95%	287	8,36%
A+	50	14,16%	1123	32,71%
A	37	10,48%	589	17,16%
A-	57	16,15%	566	16,49%
B+	65	18,41%	29	0,84%
B	53	15,01%	23	0,67%
B-	21	5,95%	8	0,23%
BB+	4	1,13%	6	0,17%
BB	13	3,68%	69	2,01%
BB-	1	0,28%	10	0,29%
BBB+	4	1,13%	262	7,63%
BBB	4	1,13%	266	7,75%
BBB-	3	0,85%	102	2,97%
CCC+	2	0,57%	2	0,06%
Total	353		3433	

Note: Credit ratings are based on S&P's credit rating scale.

5.2. Correlation statistics

To assess any potential for multicollinearity, correlation tests were conducted. Table 4 displays the correlation tests for the all the dependent and independent variables in the regression. No significant multicollinearity was detected as the correlation between all variables tested in the same regressions were all below 0.7. For the variables with a correlation above 0.7 these constitute alternative measures and are run in separate regressions.

Table 4. Correlation matrix for regression variables.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) CAR MFM	-																	
(2) CAR MAM	-	-																
(3) CAR MPR	-	-	-															
(4) CAR MPI	-	-	-	-														
(5) SIZE (ln)	-0.127***	-0.044*	-0.131***	-0.127***	1.000													
(6) ROA	-0.053***	-0.018	-0.046***	-0.039*	-0.015***	1.000												
(7) LEV	0.066***	0.109***	0.128***	0.134***	0.166***	-0.308***	1.000											
(8) INT_COV	0.006	-0.007	-0.023	-0.016	0.211***	-0.252***	0.210***	1.000										
(9) INTANG	-0.100**	0.052***	0.004	-0.006	-0.016***	0.196***	-0.044***	-0.198***	1.000									
(10) LOSS	-0.016	0.124***	0.173***	0.119***	-0.122***	-0.211***	-0.025***	-0.030***	-0.045***	1.000								
(11) NIG	0.034	0.021	0.081***	0.019	-0.298***	-0.041***	-0.063***	-0.063***	-0.010***	0.073***	1.000							
(12) FIRST	-0.006	-0.002	0.017	-0.002	-0.130***	0.058***	-0.044***	-0.078***	0.061***	-0.011***	0.061***	1.000						
(13) COV	-0.075***	-0.014	-0.014	-0.023	-0.189***	0.218***	-0.266***	-0.514***	0.178***	0.053***	0.040***	-0.017***	1.000					
(14) END_MAT	-0.008	0.038	0.021	0.036	0.158***	-0.087***	0.139***	0.129***	0.011***	-0.029***	-0.041***	-0.052***	-0.259***	1.000				
(15) IPO	-0.049***	0.051***	0.008	0.021	-0.022***	0.046***	0.016***	-0.006*	0.019***	0.054***	-0.004	0.107***	0.087***	-0.046***	1.000			
(16) RANK	0.035	-0.050**	-0.018	-0.020	-0.049***	-0.019***	0.046***	-0.083***	-0.005	0.050***	-0.153***	0.053***	0.047***	-0.050***	0.024***	1.000		
(17) TOP25	-0.062***	0.047**	0.009	0.022	0.191***	0.053***	-0.089***	0.053***	0.034***	-0.011***	0.031***	-0.068***	-0.045***	-0.063***	-0.044***	-0.721***	1.000	
(18) BOT25	0.043*	-0.020	-0.002	0.003	0.043***	-0.040***	-0.039***	-0.062***	-0.011***	0.075***	-0.172***	0.017***	0.032***	-0.070***	-0.055***	0.760***	-0.318***	1.000

*** *p<0.01*, ** *p<0.05*, * *p<0.1*. (ln) indicates that the variable has been transformed using the natural logarithm. The correlation with the different dependent variables is naturally disregarded, but reported in the same table to limit the number of tables.

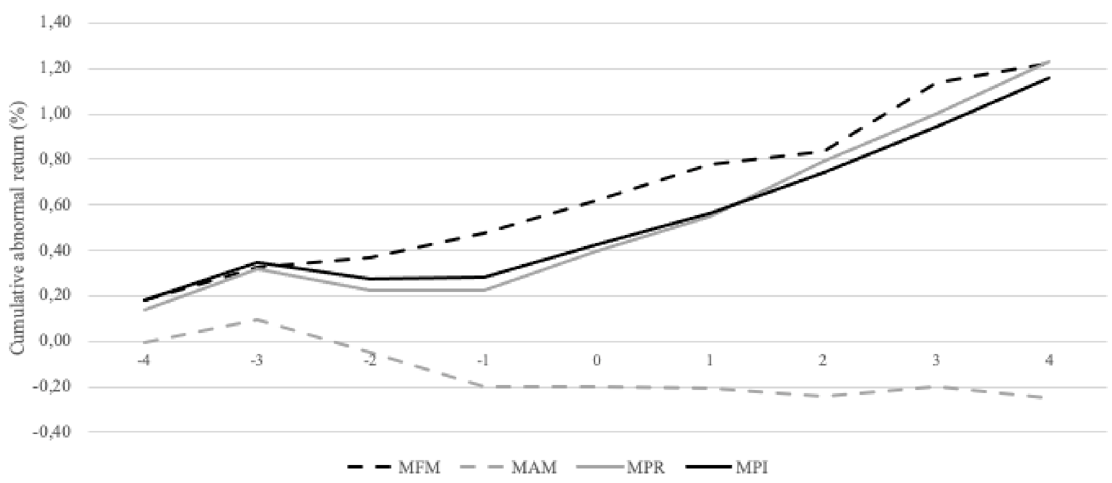
6. Results

This section presents the main results on the short horizon and long-run horizon reaction to the announcement of the list as well as additional robustness checks. All results are based on the sample where the daily return is constructed based on the price weighted by trade size for all trades larger than $100'000. We also report the findings for the sample based on the alternative method for constructing daily returns, discussed in section 6.1.2.

6.1. Short horizon returns

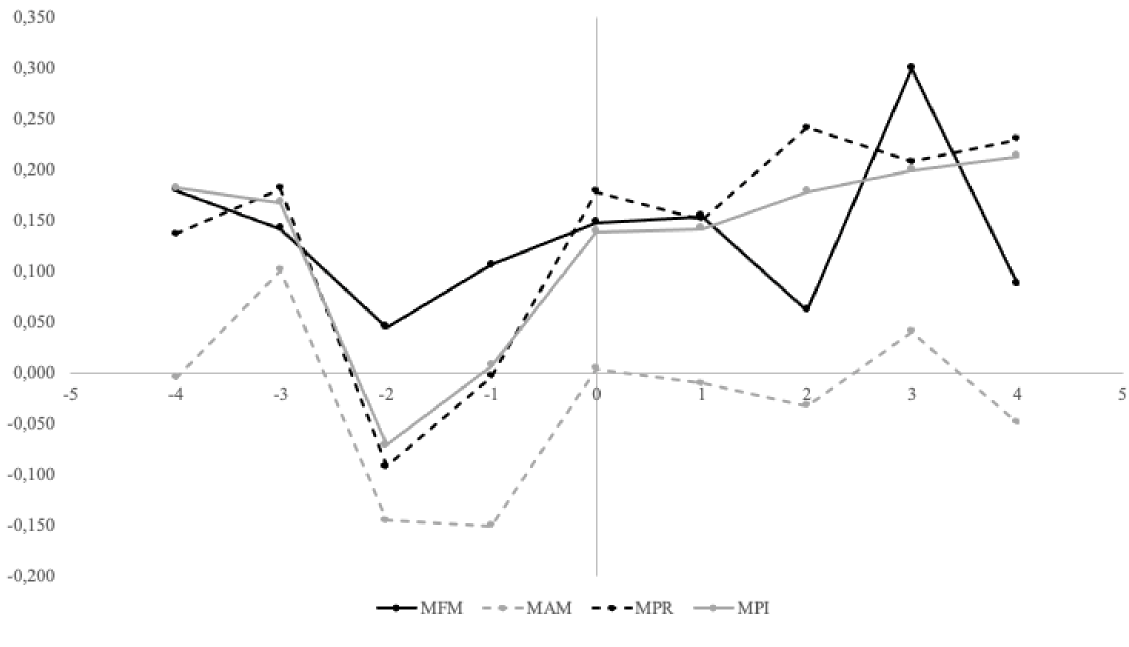
We first investigate the short horizon reaction to the list announcement on 353 firm-year observations over the period 2003-2021. Here a positive cumulative average abnormal return (CAAR) is detected over the event window (-4, 4) for the multifactor model (MFM) and both the matching portfolios models (MPI and MPR), while the mean-adjusted model (MAM) shows a negative CAAR, as can be seen in table 5 through 8. MFM displays a CAAR of 1.22%, 1.23% for the MPI, 1.15% for MPR and -0.24% for the MAM. These are significant only for MFM at the 1% level using a standardized cross-sectional t-test. When testing for significance using a nonparametric test, the sign rank test, the CAAR for MFM and both the matching portfolio models are significant at the 1% level. In terms of magnitude these cumulative returns are within what similar bond market event studies find (e.g. Marais et al., 1989). From figure 3 it is possible to discern a flatter growth in abnormal returns before the announcement of the list which transforms to a sharper incline starting the day before the announcement for MFM and both the matching portfolios. The MAM displays a continuously negative trend in abnormal returns as seen in figure 3.

Figure 3. Graph of Cumulative Average Abnormal Return (CAAR) over the event



Turning to the daily cross-sectional aggregation of the abnormal returns (AAR) which offers an interpretation of the market reaction to the announcement of the list on a per day basis during the event window. In figure 4, the average abnormal return (AAR) on the day of the announcement of the list ranges from 0.17%-0.003%. Table 5 through 8 presents the AAR over the days in the event window. On the announcement day an AAR of 0.14% for MFM is significant at the 1% level for both the standardized cross-sectional t-test and the sign rank test. MAM shows an AAR of 0.003% and is significant at the 1% level only for the standardized cross-sectional t-test. The matching portfolio based on industry exhibits an AAR of 0.17% which is significant at the 10% level with the standardized cross-sectional t-test and at 1% with the sign-rank test. The matching portfolio based on rating displays an AAR of 0.13% showing significance at the 1% level only for the sign-rank test. The AAR too displays an upward trend the day before the announcement of the list and with an upward sloping trend thereafter, which can be seen in figure 4. All of the abnormal returns display relatively similar patterns in returns close to the announcement of the list (-1, +1). In addition, the BCs experience statistically significant and positive abnormal returns before the list announcement. This given that AARs for several of the event days before the announcement for all models are frequently significant and positive. This could be a potential indicator for information leakage or investor anticipation of BCs inclusion on the list and is in line with what Filbeck & Preece (2003) finds for the list announcement on the equity market.

Figure 4. Graph of average abnormal returns (AAR) over the event window (-4, 4)



Note: Average Abnormal Returns are displayed in percentage form. For an interpretation in basis points (bps), more common in the debt markets, 1 bps equals 1/100 of a percent.

Table 5. Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) during the event window (-4, 4) for the multifactor model in percentage (%).

Day	AAR (%)	t-test (std)	Sign rank	CAAR (%)	t-test (std)	Sign rank
-4	0.180	6.74***	5.36***	0.180	0.16	5.34***
-3	0.142	10.19***	7.44***	0.322	0.49	8.85***
-2	0.045	6.74***	3.69***	0.367	0.82	9.11***
-1	0.106	8.49***	5.42***	0.473	1.26	9.65***
0	0.148	13.14***	8.46***	0.621	1.83*	10.42***
+1	0.154	13.10***	9.60***	0.775	2.47**	11.27***
+2	0.062	6.07***	4.85***	0.837	3.02**	11.52***
+3	0.300	11.73***	6.33***	1.137	4.02***	11.94***
+4	0.087	7.82***	4.53***	1.224	4.70***	12.52**

* p<0.1; ** p<0.05; *** p<0.01

Note: t-test (std) denotes the standardized cross-sectional t-test and sign rank denotes the Wilcoxon sign rank test where the test statistic for each day of the event window is presented. For the t-test (std) standardized abnormal returns have been used and where the magnitude and sign are based on unstandardized returns.

Table 6. Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) during the event window (-4, 4) for the mean-adjusted model in percentage (%).

Day	AAR (%)	t-test (std)	Sign rank	CAAR (%)	t-test (std)	Sign rank
-4	-0.005	0.64	2.61***	-0.005	0.023	2.608***
-3	0.101	1.36*	3.02***	0.096	0.083	4.174***
-2	-0.145	-4.68***	-2.02**	-0.049	-0.117	1.824*
-1	-0.150	-3.03***	-3.97***	-0.200	-0.299	-0.808
0	0.004	-3.13***	1.33	-0.196	-0.482	-0.211
+1	-0.011	-1.80**	-0.55	-0.207	-0.621	-0.365
+2	-0.033	-0.32	-0.002	-0.239	-0.698	-0.829
+3	0.040	1.27	1.97**	-0.199	-0.619	-0.536
+4	-0.049	-2.51***	-0.83	-0.248	-0.859	-1.348

* p<0.1; ** p<0.05; *** p<0.01

Note: t-test (std) denotes the standardized cross-sectional t-test and sign rank denotes the Wilcoxon sign rank test where the test statistic for each day of the event window is presented. For the t-test (std) standardized abnormal returns have been used and where the magnitude and sign are based on unstandardized returns.

Table 7. Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) during the event window (-4, 4) for the matching portfolio on rating and time to maturity in percentage (%).

Day	AAR (%)	t-test (std)	Sign rank	CAAR (%)	t-test (std)	Sign rank
-4	0.137	2.00**	4.686***	0.137	0.070	4.686***
-3	0.181	3.03***	5.645***	0.318	0.208	7.112***
-2	-0.092	-3.26***	-0.074	0.226	0.107	4.462***
-1	-0.004	0.63	1.584	0.222	0.157	4.294***
0	0.179	1.43*	5.781***	0.401	0.241	5.994***
+1	0.151	2.61**	6.083***	0.552	0.397	6.868***
+2	0.241	4.18***	4.165***	0.793	0.772	7.186***
+3	0.208	2.69***	4.236***	1.001	1.088	7.347***
+4	0.230	2.63***	4.622***	1.231	1.360	8.887***

* p<0.1; ** p<0.05; *** p<0.01

Note: t-test (std) denotes the standardized cross-sectional t-test and sign rank denotes the Wilcoxon sign rank test where the test statistic for each day of the event window is presented. For the t-test (std) standardized abnormal returns have been used and where the magnitude and sign are based on unstandardized returns.

Table 8. Average Abnormal Return (AAR) and Cumulative Average Abnormal Return (CAAR) during the event window (-4, 4) for the matching portfolio on industry and time to maturity in percentage (%).

Day	AAR (%)	t-test (std)	Sign rank	CAAR (%)	t-test (std)	Sign rank
-4	0.182	2.46***	4.483***	0.182	0.087	4.48***
-3	0.168	3.13***	5.660***	0.350	0.238	6.892***
-2	-0.071	-2.85***	0.361	0.279	0.159	4.839***

-1	0.007	1.03	2.196**	0.286	0.239	4.934***
0	0.139	0.64	4.661***	0.424	0.297	6.135***
+1	0.142	2.33**	5.980***	0.566	0.446	6.957***
+2	0.179	3.35***	3.803***	0.745	0.761	7.098***
+3	0.200	2.75***	4.364***	0.945	1.085	7.212***
+4	0.213	2.60***	4.956***	1.158	1.357	8.544***

* p<0.1; ** p<0.05; *** p<0.01

Note: t-test (std) denotes the standardized cross-sectional t-test and sign rank denotes the Wilcoxon sign rank test where the test statistic for each day of the event window is presented. For the t-test (std) standardized abnormal returns have been used and where the magnitude and sign are based on unstandardized returns.

The issue with using multiple models is interpreting the empirics with indications of differing results amongst the models. Our different models are intended to capture various risk factors and any indication of not abnormal returns consistently among all models would indicate that any abnormal return would be a compensation for that risk factor.

However, all of the models indicates that there is a positive and significant reaction, for most of the models and statistical tests, to the list on the announcement day, indicating that investors fail to immediately incorporate salient information on employee satisfaction into bond prices. Considering the cumulative effect of the list announcement on the BCs over the entire event window the different models offer to some extent evidence that higher employee satisfaction, as indicated by list inclusion, is not immediately reflected in bond prices. With only the abnormal returns for the multifactor model (MFM) being significant for both statistical tests and the matching portfolios being significant for the sign rank test support for rejecting the null hypothesis that the mean cumulative abnormal returns equal zero is relatively limited. However, the initial evidence of the markets failure to react to the announcement of the list on the announcement day remains.

A more definitive interpretation regarding our hypothesis can be inferred only after investigating whether these positive abnormal returns remain after controlling for other observable characteristics.

6.1.1. Cross-sectional tests

In addition to our first analysis, we here relate the cumulative abnormal returns to cross-sectional firm variables, in order detect any relationship between the observed cumulative abnormal return and the reaction to the announcement of the list.

Table 9. Regression results for Cumulative Abnormal Return (CAR) during the event window (-4, 4) for all benchmark models and firm-level controls

	CAR MAM	CAR MFM	CAR MPI	CAR MPR
NIG	-0.00185	0.00037	-0.00198	0.00127
	(0.40)	(0.21)	(0.39)	(0.21)
SIZE (ln)	-0.00143	-0.00104	-0.00258	-0.00248
	(1.69)*	(2.53)**	(3.03)***	(2.91)***
ROA	0.00000	-0.00008	-0.00011	-0.00013
	(0.00)	(0.70)	(0.54)	(0.59)
LEV	0.00791	0.00457	0.01013	0.01073
	(1.62)	(2.48)**	(2.48)**	(2.33)**
INT_COV	0.00000	-0.00000	-0.00000	-0.00000
	(0.06)	(1.37)	(0.79)	(1.08)
INTANG	0.00599	-0.00483	0.00328	0.00417
	(1.54)	(2.41)**	(0.87)	(1.13)
CONSTANT	0.02610	0.02980	0.06091	0.05844
	(1.59)	(1.10)	(1.73)*	(1.89)*
Year fixed effects	Yes	Yes	Yes	Yes
R2 -adjusted	0.10	0.27	0.16	0.15
N	353	353	353	353

* p<0.1; ** p<0.05; *** p<0.01

Note: Standard errors are clustered on firm. t-value is reported in parenthesis. The t-statistics that is reported is based on the standardized cumulative abnormal return (SCAR) and the sign and magnitude is based on unstandardized cumulative abnormal return (CAR). (ln) indicates that the variable has been transformed by the natural logarithm.

All models display a positive cumulative abnormal return however their significance differs from the above results in table 5 through 8. The previously significant cumulative abnormal return for the multifactor model does not remain when introducing firm specific factors that could influence the returns. Cumulative abnormal returns for the two matching portfolios are weakly significant at the 10% level as can be seen in table 9. As expected, the SIZE variable is negatively related to returns and significant for all models. In addition, the LEV variable shows a positive relationship to returns as predicted and is significant at the 5% level for MFM and both matching portfolios. All other variables are found to not be statistically significant but do however follow our expectations in explaining the returns. The coefficients for these variables are low, suggesting the marginal impact on the overall returns, which can also be inferred from the low adjusted r-squared across the different models.

Given that the results from the regression after including control variables do not remain significant for the multifactor model suggests that the above factors rather than the actual inclusion on the list would be driving the abnormal returns we previously observed. The low significance at the 10% level for the matching portfolios as well as the other models not showing any significant results is not offering conclusive evidence in favor of supporting our alternative hypothesis that higher employee satisfaction, as demonstrated through the announcement of list inclusion is not immediately reflected in bond prices. We thus fail to reject the null hypothesis that the mean cumulative abnormal returns equal zero.

We have here focused on the cross-sectional analysis of the cumulative abnormal return and not the cross-sectional abnormal returns for each day (AAR), as the examination of pre and post event returns provides better information on market efficiency (Kothari & Warner, 2007). However, in the appendix we provide tables on the same cross-sectional regressions as above but on cross-sectional abnormal returns but for each event day (i.e. AAR). These regression results indicate that the AAR is weakly significant at the 10% level for the two matching portfolios at the announcement day and for three of the models two days before announcement. This would indicate an information leakage, but do not remain after introducing further robustness checks.

In order to rule out any spurious relationships as well as testing whether the results from the regression in table 9 are robust, we introduce other observable characteristics and model specifications.

6.1.2. Robustness checks

As argued in section 4.4.4., several bond-level characteristics could be influencing the abnormal returns that we observe. In table A.83. in the appendix we present the regression results when controlling for bond IPO underpricing driving any abnormal return, in addition to the number of covenants a firm tend to experience as well as any influencing effect from bonds maturing closely to the announcement of the list. We find that there is no significant relationship between any of the bond-level controls and the regression results in table A.83. in the appendix is in line with the results found in the main section above. Noticeable is that the COV variable, indicating the tendency for a firm being limited in its actions by debt covenants, displays a negative relationship contrary to our expectations, however not being significant rendering any further inferences inordinate.

Firms' ability to repay debt is a central part of the pricing of debt and as such this study naturally takes this into account in various ways. However, as previously mentioned employee satisfaction might be negatively perceived by debtholders for firms with financial constraints. A clear signaling of making a loss prior to being included in the list would signal a degree of distress potentially leading to an effect not previously captured. We adjust our model by adding a dummy to controls for this, yet the results remain unaffected (See table A.84 in appendix). The number of firms within our sample experiencing a loss is small, which should be noted, and therefore any stronger interpretation regarding this potential effect should be limited. Though not reported here we additionally test for any agency concerns by using a dummy if the firm has adopted a poison pill, this as a proxy for corporate governance and any agency concerns. As the data was limited on this and we have few data points we stress that conclusion regarding this is not ordinate. The results remain after controlling for this.

Previous studies on the BCs have not investigated the different ranking attributes of the list. Higher ranked firms tend to see more intense publicity as well as any first-year firm appearing on the list would see higher abnormal returns if mispricing is persistent. The marginal effect of a better position in the ranking could mean an influencing effect on abnormal returns. As can be seen in table A.85. in the appendix, the results remain, except for increased significance for the two matching portfolios at the 5% level when including list-level. However, as indicated in table A.86. these effects disappear when we run all control variables and the main results remain robust. None of the list-level variables are significant and noticeably they indicate a negative relationship. Similarly, we control for the lower 25 on the ranking with no effect compared to the main results as well as running the regression individually with each list-level variable without any differing results.

Not reported here we additionally use a different measure for credit rating by using the numerical issue rating instead of the NIG variable but with no significant effect on the overall results.

As mentioned in section 4.3.1, we have consistently carried out the study using two different methods for constructing the daily returns. One based on the last price for all trades and one, favored by (Bessembinder et al., 2009) and used in our study, the other based on the price weighted by each trade's size for all trades larger than $100'000 (For further discussion on this see 4.3.1). These two samples are highly correlated, and the summary statistics vary minimally. As a further robustness all analysis has been conducted on both samples, and although not reported here the findings from the previous section does not differ from those based on the last price for all trades.

6.2. Long-run horizon returns

We now turn to examine the nature of the returns to the list announcement and employee satisfaction in the long-run horizon. Even though we find no evidence of abnormal returns in the short-horizon it is imperative to consider any corrections or long-run effects.

The cross-section of all Buy-and-Hold Abnormal Returns (BHAR) in table 10 shows positive abnormal returns ranging from 0.12%-0.19% over both matched portfolios for all periods but none of these are significant for any of the event windows. This would suggest that there is no subsequent correction by the market after the list is announced.

Table 10. Buy-and-Hold Abnormal Returns (BHARs) post announcement in 12 different event windows from 0-30 up to 0-360. In percentage (%).

Event day	BHAR MPR (%)	BHAR MPI (%)	t-test MPR	t-test MPI
0-30	0.116	0.119	0.632	0.652
0-60	0.180	0.171	0.979	0.938
0-90	0.179	0.170	0.977	0.932
0-120	0.190	0.180	1.038	0.992
0-150	0.193	0.182	1.049	1.000
0-180	0.189	0.179	1.028	0.982
0-210	0.185	0.176	1.008	0.967
0-240	0.181	0.172	0.984	0.944
0-270	0.177	0.170	0.967	0.935
0-300	0.179	0.171	0.976	0.942
0-330	0.180	0.173	0.983	0.950
0-360	0.185	0.176	1.006	0.969

* $p<0.1$; ** $p<0.05$; *** $p<0.01$

Note: t-value from t-test is using the adjusted unbiased standard deviation that has been adjusted for cross-correlation among returns between firms. For further detail on this see section 4.5.2.

For the long-run price performance of 'The BC portfolio' table 11 displays the abnormal returns over the matched benchmark portfolios to holding 'The BC portfolio' with yearly rebalancing during 2003-2021. These display a return of 0.225% over the industry matched portfolio and 0.233% over the ratings matched portfolio. None of these are significant. We provide standalone annual returns over each matched benchmark portfolio for each year as well. None of the standalone annual return are significant.

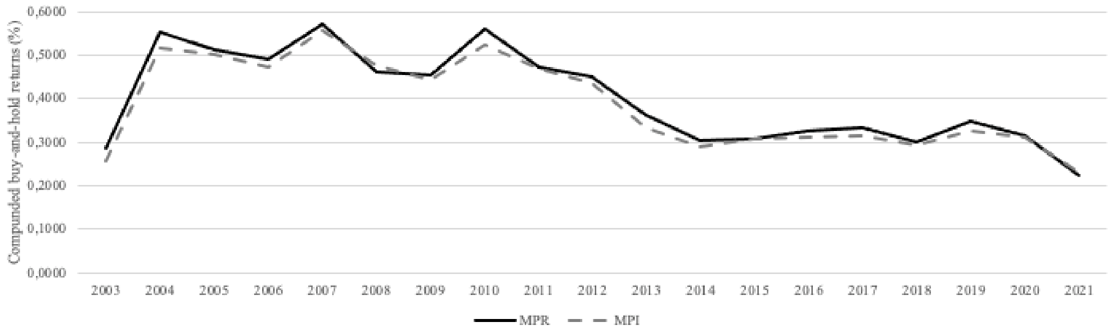
Table 11. Buy-and-Hold-Abnormal-Return for holding 'The BC portfolio' with yearly rebalancing during 2003-2021 over the matched benchmark portfolios. In percentage (%).

Year	Annual MPI (%)	Annual MPR (%)	BAHR MPI (%)	BAHR MPR (%)	t-test MPI	t-test MPR

2003	0.285	0.258	0.285	0.258	0.365	0.333
2004	0.265	0.259	0.551	0.518	0.705	0.668
2005	0.247	0.243	0.513	0.502	0.657	0.649
2006	0.241	0.230	0.489	0.474	0.626	0.612
2007	0.327	0.324	0.569	0.555	0.729	0.716
2008	0.133	0.151	0.461	0.476	0.590	0.614
2009	0.319	0.291	0.452	0.443	0.579	0.572
2010	0.240	0.233	0.559	0.525	0.716	0.677
2011	0.231	0.237	0.472	0.470	0.604	0.607
2012	0.220	0.200	0.452	0.437	0.579	0.564
2013	0.143	0.134	0.364	0.334	0.466	0.431
2014	0.160	0.157	0.303	0.290	0.388	0.375
2015	0.150	0.152	0.309	0.309	0.396	0.399
2016	0.175	0.158	0.324	0.310	0.416	0.401
2017	0.160	0.157	0.335	0.315	0.429	0.407
2018	0.139	0.136	0.300	0.293	0.384	0.378
2019	0.208	0.191	0.348	0.327	0.445	0.423
2020	0.107	0.122	0.316	0.313	0.404	0.404
2021	0.117	0.111	0.225	0.233	0.288	0.301

* p<0.1; ** p<0.05; *** p<0.01

Note: t-value from t-test is using the adjusted unbiased standard deviation that has been adjusted for cross-correlation among returns between firms. For further detail on this see section 4.5.2.



Note: Average Abnormal Returns are displayed in percentage form. For an interpretation in basis points (bps), more common in the debt markets, 1 bps equals 1/100 of a percent.

Thus, with none of the abnormal returns being significant we fail to reject the null hypothesis that the mean Buy-and-Hold Abnormal Returns equal zero. This would indicate that there is no subsequent correction by the bond market and that there is no long-run outperformance of bonds issued by BCs. This would further suggest that the market seems to immediately incorporate the value of employee satisfaction into bond prices.

7. Discussion

The following section elaborates on the above presented results and its implications with the aim to answer and discuss the research question. The final parts of the analysis develop on the limitations of the paper.

The table 12 below expands on the different underlying assumptions needed to be true in order to explain our results and its associated interpretation on how the bond market values employee satisfaction as well as the implication for an efficient market. Thereafter we discuss each explanation's assumptions and its likelihood.

Table 12. Overview of the different explanations for our findings.

Explanation I		
Assumptions	**Interpretation (Given our results)**	**EMH implications**
i) Information on employee satisfaction is value relevant for bondholders, because of its effect on firms' financial capacity, risk and ability to meet its financial obligations. ii) The announcement of BC list inclusion poses new and value relevant information to bond investors.	The bond market immediately reacts to and incorporates the information into bond prices, why it does not result in any abnormal returns. The BC list inclusion works as a valid tool of signaling for companies to reduce information asymmetry. It serves as an observable cue for bond investors to infer information about the firm's risk profile and ability to meet its financial obligations.	The efficient market hypothesis is true.
Explanation II		
Assumptions	**Interpretation (Given our results)**	**EMH implications**
i) Information on employee satisfaction is value relevant for bondholders, because of its effect on firms' financial capacity, risk and ability to meet its financial obligations. ii) The announcement of BC list inclusion poses value relevant, but not new information to bond investors.	Investors do not react to the information on BC list inclusion, because investors have already drawn on other observable cues to infer information about employee satisfaction on the firm's ability to repay debt, meaning that the information on employee satisfaction is already incorporated in bond prices, why we see no abnormal returns. The BC list inclusion serves to confirm already existing information. Hence, the BC list inclusion does not function as a signaling tool.	The efficient market hypothesis is true.

Explanation III		
Assumptions	**Interpretation (Given our results)**	**EMH implications**
i) Bond investors erroneously do not perceive any link between employee satisfaction and firms' financial capacity and ability to meet its financial obligations. ii) The bond investors do not perceive the BC list inclusion as value relevant, when actually it provides new and value relevant information.	Investors do not react to the information on list inclusion. Employee satisfaction is not reflected in bond prices, for why no abnormal returns are observed.	The efficient market hypothesis is not true given that i) employee satisfaction is beneficial to firm's ability to repay debt and ii) the BC list is a sufficient proxy for employee satisfaction.

The interpretations in table 12 above relies on our inherent assumption that employee satisfaction is value relevant for investors in the bond market. However, such an avenue would call into question many of the several findings on both the relationship between pricing of debt and employee satisfaction and those claiming employee satisfaction leads to positive operating and financial performance and a lower risk profile. We see this as a less plausible explanation levering on the central argument on the importance of efficient human resource management in the human capital intense firm of the 21st century. This renders *Explanation III* redundant.

Explanation I: BC list inclusion perceived as new and value relevant information

Given *Explanation I*, described in Table 12, the findings in our study indicates that the bond market immediately reflects high employee satisfaction, as indicated by inclusion on the list, into bond prices. This is evident in both the short-horizon and a longer horizon. The mechanisms with which this is achieved can be related to actions dealing with information asymmetry: signaling, from the firm, and screening, by the investors.

Employee satisfaction would act as a valid form of signaling, as it incurs costs, by the firm when included on the list. As employee satisfaction has been connected to lowering various forms of risk (Bauer et al., 2009; Francis et al., 2019) the signal of high employee satisfaction should convey important risk information to bond investors, namely that the firm has lower risk. A decline in assessed risk implies an increase in the bond prices, and thus a positive abnormal return if the market would fail to incorporate this. However, as indicated in our results, given explanation I, the potential future benefit of employee satisfaction is incorporated into bond prices as the list contains new information when firms are included on the BC list producing a "lack of" abnormal returns.

Our results also do not indicate that there are any corrections to the initial list announcement nor any abnormal long-run performance to holding the equal weighted 'The BC portfolio'. This follows understandably by the same interpretation as above.

With the argument that the bond market reflects this information into bond prices and thus any correction or trading strategy based on employee satisfaction would not yield abnormal returns. As with any trading strategy, its robustness in implementation would also have to be assessed in relation to transaction costs. As the abnormal returns reported in the results, are small any outperformance above transaction would seem unlikely.

Explanation II: BC list inclusion perceived as value relevant, but not new information

Previous literature points towards human resource practices being a feature of a lender's process of evaluation (Datta et al., 1999; Marsh & Shaiman, 2022). Screening theory would emphasize that employee satisfaction is an observable characteristic and various human relations practices can be used as a screen by bond investors. To wit, a favorable employee relations screen would serve to reduce information asymmetry relating to a firm's risk profile and therefore a more informed investment decision. Qian et al (2021) findings emphasize that employee satisfaction could serve as a screen, not only for the firm's quality, but also for their intent and treatment of key stakeholders. The bond market, as other lenders, in its screening process, we would argue, interpret this information as lower risk and thus incorporates it into bond prices. In turn this would mean that high employee satisfaction as indicated through list inclusion is information on a firm's intangible that bond investors have already valued.

The mechanisms with which the bond market would have already incorporated employee satisfaction into bond prices relies on that the cues and signals are observable to the same degree as the information provided by the list. This could be deemed reasonable, as several human relations practices (benefits, salaries, labor disputes, union activities and other public information) is information readily available to investors. However, the BC list serves as collective output measure of employee satisfaction, as compared to a lot of the other public information which is input related. To a certain degree, one could liken the list with a credit rating. Employee satisfaction is not a permanent characteristic, as is credit worthiness, and as such continuous independent verification seems plausible. The argumentation that the list then adds new and relevant information is therefore more likely and we conclude that the *Explanation I* would seem more plausible.

Conflicting findings with the equity market

On the one hand, our results are in line with previous literature's findings on the debt market (both private and public) (Bauer et al., 2009; Francis et al., 2019; Chen et al., 2019), namely that debtholders do seem to incorporate employee satisfaction into prices of debt. On the other hand, both the first and the second explanation of our results contradict the previous findings on employee satisfaction in the equity market (Boustanifar & Kang, 2022; Edmans, 2011; Filbeck & Preece, 2003). Comparable studies to ours on how the bond market value intangibles are scarce, and our results therefore highlight the value of investigating the implications on the bond market. The earliest research on the equity market cited imperfect information dissemination of employee satisfaction as the explanation for finding abnormal returns. However, Edmans (2011) argues that this is a failure by equity markets to incorporate the value of an intangible into prices and that intangibles only affect value when manifested in subsequent tangible outcomes such as earnings announcement.

However, regardless of which one of *explanation I* and *II* holds true they do not account for the contradicting findings compared to the equity market as this signal and screen is readily available to equity holders too. A key difference between bond investors and equity investors is the asymmetric pay-off structure due to carrying a fixed claim on the firm's net assets. Concerned with the downside risk bond investors could be argued to interpret the signal differently from equity investors as the benefit of employee satisfaction would offer protection towards adverse events.

Drawing on support from the asset-substitution theory, overall shareholders, as the residual claimants, lose out when investors reconsider their risk assessments downward, whereas bondholders, as holders of a senior claim, benefit from a decrease in risk evaluations (Kliger & Sarig, 2000). This could present justification for the conflicting interpretation of the same signal/screen. Equity investors could still perceive employee satisfaction as a positive signal but only values it, as Edmans (2011) argues, when it manifests in tangible outcomes (such as earnings) in the future. Bond investors would thus incorporate information on employee satisfaction into bond prices and the announcement of the list would not yield any abnormal returns. This could serve to explain the contradiction of our finding in relation to the findings on the equity market.

7.1.1. Limitations

Naturally this study has limitations both related mainly to the inherent assumptions of an event study research method, and methodological considerations for estimating abnormal returns.

An event study's inherent assumption relies on the notion that the estimated "normal" (or expected) return is the true return if the event would not have occurred. As such any test on market efficiency is ultimately also a test of models of expected returns, and vice versa. All models used for calculating "normal" returns is only as (Fama, 1998, p. 291) expresses it *"incomplete descriptions of the systematic patterns in average returns during any sample period".*

The "bad-model" issue is a duly noted issue by the research field and is however less severe for the results of our short horizon event study as the expected returns on a daily basis are small, having a limited effect on abnormal returns (Fama, 1998). The "bad-model" issue is exacerbated for a growing event horizon, which would call any significant results from our long-run horizon event study into question. Furthermore, depending on the choice of model subsequent choice of estimation period (if any) results in a trade-off between the accuracy of estimation and potential changes in parameters. Given the infrequent trading of bonds satisfactorily deriving estimation parameters for the different expectations models relying on historical returns can pose limitations. As this is a market characteristic inherent in the sample it is difficult to resolve. For studying our research question, it would be suitable to study a sample which inherently without bias ensure larger corporations, such as the ones in the Best Companies to Work For list, to increase liquidity and observations within the estimation period.

Two of the models used for estimating the expected returns rely on matching each bond at a given time to an index (based on both rating and industry). Both the choice of index and matching of each bond on a fine grain level is sensitive to bias.

Another implicit assumption when using the event study methodology relies on the lack of competing information during the event window, i.e., that no unrelated events occur around the list announcement. Using a larger event window for studying the effect of the list announcement on returns fundamentally increases the probability for other unrelated "events" influencing any abnormal returns. This would void the validity of the results. To defer any such confounding effects we examine a sub-sample of our firms' press release libraries during the event window period and see that any firm specific information unrelated to the event is relatively limited. However, other general market-wide news could present noise during the event window, undermining the assumption of no competing information and thus poses a limitation.

Investigating the reaction by the bond market (and any other capital market) to the value of employee satisfaction, is based on the condition that the list announcement is unanticipated by the market and not previously incorporated into the prices of bonds. By examining the market's reaction in the days preceding the list announcement any such anticipation is captured, as is evident in the significant positive abnormal in the days preceding the announcement. However, the degree to which the list announcement is anticipated could vary from firm to firm. Several firms reappear on the list during longer periods and as such, ceteris paribus, would render the list inclusion predictable for some firms. When controlling for various observable characteristics these abnormal returns (AAR) diminish, indicating that they relate to compensation for other factors than the list for example size or leverage.

As with any quantitative research there is a possibility of data handling errors. Nonetheless conducting a bond market event study over a longer sample period involves processing a large number of individual bonds and aggregating this data in several steps to the level where the actual analysis is carried out. This increases the risk for data handling errors.

8. Concluding remarks

This section describes the most important conclusions of the study in relation to the research question, highlights the contributions of the study and finally, presents suggestion for future research.

8.1. Conclusion

Human capital is arguably an ever-increasing important asset for firms and understanding how capital providers values this intangible asset is therefore important. This study has therefore aimed at examining how the bond market reflects the value of intangibles, in particular human capital and by looking at employee satisfaction. We do so by observing the bond market's reaction to the announcement of Fortune Magazines '100 Best Companies to Work For' list, a public and highly salient measure of employee satisfaction, over the years 2003-2021.

There appears to be some evidence of an initial lack of reaction on the announcement day, leading up to the announcement and cumulative abnormal return over the event window, as evidenced by finding statistically significant abnormal returns. However, notably these returns do not remain when controlling for firm and bond specific characteristics. This would suggest factors, other factors than the announcement of the list, explain the abnormal returns, and that the bond market ultimately reflects the value creation of employee satisfaction.

When also investigating the long-run returns after the list announcement, 1-12 months, and do not find evidence of abnormal returns. This further supports the above results that high employee satisfaction is reflected in the prices by the bond market. Additionally holding an equally weighted portfolio of bonds issued by BCs over the sample period with yearly rebalancing when a new list is announced did not yield any statistically abnormal performance compared to two matching portfolios on rating and industry.

The results follow previous literature on the pricing of debt namely that debtholders do seem to incorporate employee satisfaction into prices of debt. Interestingly, the result suggests that the bond market values employee satisfaction in a differing way than the equity market. This could be explained by the difference in the asymmetric pay-off structure between equity holders and debt holders, as the latter carries a fixed claim on the firm's net assets. Being concerned with the downside risk bond investors could be argued to interpret the signal differently from equity investors as the benefit of employee satisfaction would offer protection towards downside risk (e.g. adverse events). Shareholders, as the residual claimants, lose out when investors reconsider their risk assessments downward, whereas bondholders, as holders of a senior claim, benefit from a decrease in risk evaluations. Employee satisfaction could still be perceived by equity holders as a positive signal but only values it, as Edmans (2011) claims, when it manifests in tangible outcomes (such as earnings announcements).

This differing view on the value of employee satisfaction between the bond market and the equity market highlights the need to further understand how the bond market values other intangibles. We hope our findings will contribute to further research on this.

8.2. Contribution

This study makes two contributions. Firstly, it expands on previous literature supporting evidence that bondholders seem to pay attention to employee satisfaction and incorporates its benefit into debt prices. This has shed light on how bondholders view the trade-off between the costs and benefits of employee treatment, especially in the public market setting where information asymmetry is higher.

Secondly, comparing our results to previous findings in the equity market on the incorporation of employee satisfaction has highlighted a difference in how capital providers values an intangible, human capital. This contributes to furthering our understanding on the wealth effect between different capital providers.

8.3. Future research directions

The overall scarcity of bond market event studies highlights a gap in understanding other capital provider's wealth effects from different corporate events. Addressing this becomes more important when considering the size and importance of the bond market in providing capital. The findings in this study that suggests the bond market incorporates employee satisfaction in bond prices, as compared to the equity market that seems to fail to do so. This opens up the question on how the bond market values other intangibles than human capital. Several studies on the equity market on for example R&D (Chan et al., 2001; Lev & Sougiannis, 1996), advertising (Chan et al., 2001), patent citations (Deng et al., 1999), and software development costs (Aboody & Lev, 1998) indicates abnormal returns and seemingly market inefficiencies. Investigating these intangibles but in a bond market setting would present further evidence towards how the bond market reflects the value of intangibles.

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Appendices

OLS assumption tests

The OLS regression model makes certain assumptions about the characteristics of the underlying data, including unlikelihood of large outliers, residuals with a mean of 0, observations are independently and identically distributed random variables, no perfect multicollinearity and homoskedasticity (Stock, 2020). Violation of any of the assumptions may therefore result in lower validity of the findings, why it is tested for.

Shapiro Wilk test for Normality

Shapiro Wilk test the null hypothesis that the distribution of the residuals is normal. The results show that the null hypothesis that the residuals are normally distributed can be rejected for all of the four specifications of standardized abnormal returns.

Table A.1. Shapiro Wilk test

Variable	Obs	W	V	z	Prob>z
SCAR_MAM_r	1,836	0.717	310.325	14.549	0.000
SCAR_MFM_r	1,836	0.969	33.579	8.910	0.000
SCAR_MPR_r	1,836	0.824	193.210	13.348	0.000
SCAR_MPI_r	1,836	0.830	186.391	13.257	0.000

Note: The normal approximation to the sampling distribution of W' is valid for 4<=n<=2000.

VIF test to control for no perfect multicollinearity

The variance inflation factor (VIF) measures the magnitude of multicollinearity in a regression analysis, which appears in cases where correlation exist between independent variables in a multiple regression analysis. A low VIF value indicates a low probably of multicollinearity.

Table A.2 VIF test

	SCAR_MFM		SCAR_MAM		SCAR_MPR		SCAR_MPI	
	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF	VIF	1/VIF
COV	1.463	.683	1.463	.683	1.463	.683	1.463	.683
INT_COV	1.428	.7	1.428	.7	1.428	.7	1.428	.7

ROA	1.268	.789	1.268	.789	1.268	.789	1.268	.789
SIZE	1.225	.816	1.225	.816	1.225	.816	1.225	.816
LEV	1.193	.839	1.193	.839	1.193	.839	1.193	.839
NIG	1.13	.885	1.13	.885	1.13	.885	1.13	.885
LOSS	1.124	.89	1.124	.89	1.124	.89	1.124	.89
END_MAT	1.074	.931	1.074	.931	1.074	.931	1.074	.931
INTANG	1.073	.932	1.073	.932	1.073	.932	1.073	.932
FIRST	1.052	.95	1.052	.95	1.052	.95	1.052	.95
IPO	1.047	.955	1.047	.955	1.047	.955	1.047	.955
Mean VIF	1.189	.	1.189	.	1.189	.	1.189	.

Breusch–Pagan/Cook–Weisberg test for homoskedasticity

Breusch Pagan tests the null hypothesis of the error terms having constant variance. For all of the four specifications of standardized abnormal returns, the null hypothesis of error terms having constant variance can be rejected, thus confirming the alternative hypothesis that heteroskedasticity is present.

Table A.3. Breusch–Pagan/Cook–Weisberg

Variable	**H0**	**chi2(1)**	**Prob > chi2**
SCAR MFM	Constant variance	85.27	0.0000
SCAR MAM	Constant variance	52.45	0.0000
SCAR MPR	Constant variance	41.12	0.0000
SCAR MPI	Constant variance	40.50	0.0000

Breusch Godfrey test for serial correlation

Tests the null hypothesis of no autocorrelation. For all of the four specifications of standardized abnormal returns, the null hypothesis of no autocorrelation can be rejected, indicating that autocorrelation exists.

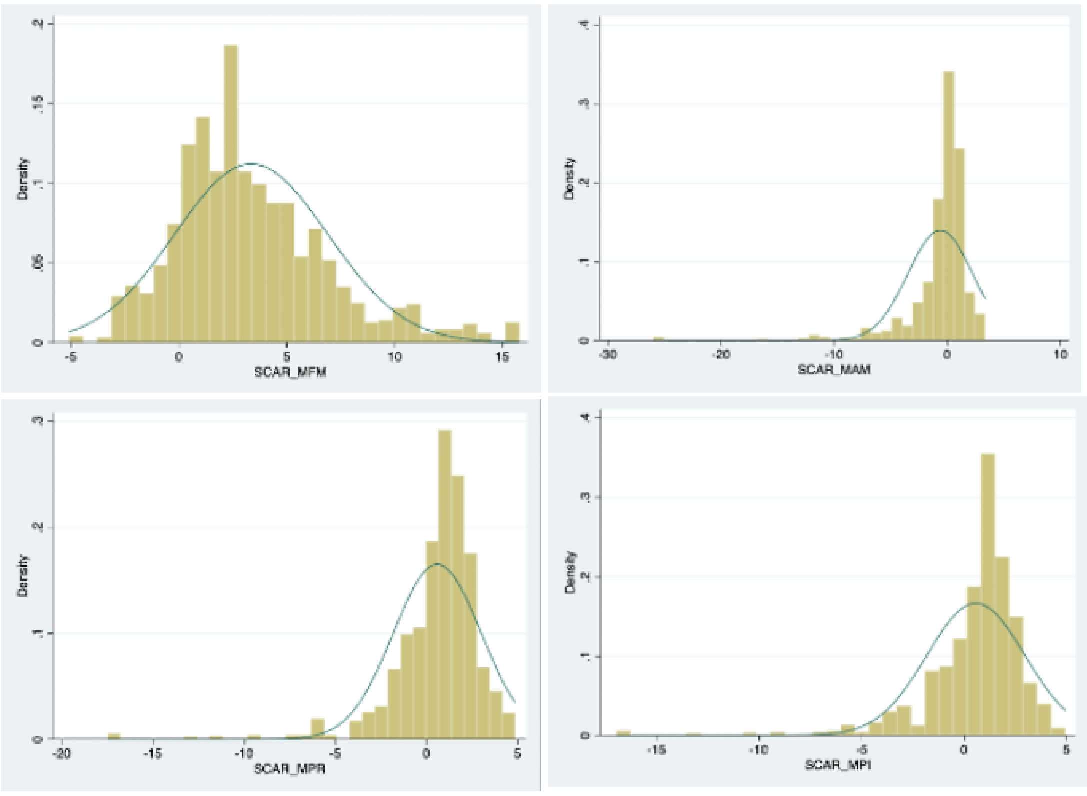
Table A.4. Breusch Godfrey test

Regression model	**Chi2**	**Df**	**Prob>Chi2**

SCAR_MFM	1493.648	2	0.000
SCAR_MAM	1497.349	2	0.000
SCAR_MPR	1490.270	2	0.000
SCAR_MPI	1490.464	2	0.000

Graphical illustration of the distribution of dependent variables

Figure A.1. Standardized Abnormal Returns Histogram



Descriptive information of dataset

Number of firms and bonds per year

Table A.5. Descriptive data of sample set

Year	Number of firms	Number of bonds	Event date
2003	21	80	2003-01-06
2004	16	68	2003-12-29

2005	17	68	2005-01-10
2006	13	60	2006-01-09
2007	14	63	2007-01-08
2008	14	57	2008-01-22
2009	12	59	2009-01-22
2010	17	96	2010-01-21
2011	18	117	2011-01-20
2012	21	135	2012-01-19
2013	20	235	2013-01-16
2014	22	240	2014-01-16
2015	17	233	2015-05-03
2016	15	199	2016-03-03
2017	20	312	2017-03-09
2018	24	364	2018-02-15
2019	21	336	2019-02-15
2020	19	355	2020-02-18
2021	32	356	2021-04-12
Total	353	3433	
Mean	19	181	
Unique	78		

List of all sample firms

Table A.6. List of all '100 Best Companies to Work For' included in the sample

Company Name	Industry	Public/Private	No. of times on the list
AT&T Inc.	Telecommunications	Public	2
AbbVie Inc.	Health Care	Public	4
Activision Blizzard, Inc.	Technology	Public	2
Adobe Inc.	Technology	Public	10
Aflac Incorporated	Insurance	Public	14
Alphabet Inc.	Technology	Public	6

American Express Company	Banks	Public	18
Amgen Inc.	Health Care	Public	3
Autodesk, Inc.	Technology	Public	5
Bank of America Corporation	Banks	Public	3
Baxter International Inc.	Health Care	Public	1
BayCare Health System, Inc.	Health Care	Private	1
Cadence Design Systems, Inc.	Technology	Public	6
CalAtlantic Group, Inc.	Construction & Materials	Private	2
Capital One Financial Corporation	Banks	Public	11
Chesapeake Energy Corporation	Oil & Gas	Public	7
Cisco Systems, Inc.	Technology	Public	15
Citrix Systems, Inc.	Technology	Private	1
Colgate-Palmolive Company	Personal & Household Goods	Public	2
Comcast Corporation	Telecommunications	Public	4
Credit Acceptance Corporation	Banks	Public	6
CrowdStrike Holdings, Inc.	Technology	Public	1
Darden Restaurants, Inc.	Travel & Leisure	Public	4
Delta Air Lines, Inc.	Industrial Goods & Services	Public	3

Devon Energy Corporation	Oil & Gas	Public	9
EOG Resources, Inc.	Oil & Gas	Public	6
Elevance Health Inc.	Insurance	Public	1
Eli Lilly and Company	Health Care	Public	4
FedEx Corporation	Industrial Goods & Services	Public	11
First American Financial Corporation	Insurance	Public	4
First Horizon Bank	Banks	Private	1
Genentech, Inc.	Health Care	Private	2
General Mills, Inc.	Food & Beverage	Public	10
Guidant LLC	Health Care	Private	1
Hasbro, Inc.	Personal & Household Goods	Public	3
Hewlett Packard Enterprise Company	Technology	Public	1
Hilton Worldwide Holdings Inc.	Travel & Leisure	Public	2
Hyatt Hotels Corporation	Travel & Leisure	Public	8
Intel Corporation	Technology	Public	3
International Business Machines Corporation	Technology	Public	3
Intuit Inc.	Technology	Public	10
Kimberly-Clark Corporation	Chemicals	Public	1

L3Harris Technologies, Inc.	Technology	Public	1
MBNA Corp.	Banks	Private	3
Marriott International, Inc.	Travel & Leisure	Public	18
Mastercard Incorporated	Banks	Public	1
Mattel, Inc.	Personal & Household Goods	Public	5
Medtronic plc	Health Care	Public	1
Merck & Co., Inc.	Health Care	Public	3
Microsoft Corporation	Technology	Public	5
Monsanto Company	Food & Beverage	Private	3
Mr. Cooper Group Inc.	Banks	Public	1
NIKE, Inc.	Personal & Household Goods	Public	1
NVIDIA Corporation	Technology	Public	5
NetApp, Inc.	Technology	Public	2
Nordstrom, Inc.	Retail	Public	16
Northwell Health, Inc.	Health Care	Private	1
OhioHealth Corporation	Health Care	Private	1
Oracle America, Inc.	Technology	Private	1
Pfizer Inc.	Health Care	Public	2

PulteGroup, Inc.	Construction & Materials	Public	1
Regeneron Pharmaceuticals, Inc.	Health Care	Public	1
Salesforce, Inc.	Technology	Public	3
ServiceNow, Inc.	Technology	Public	1
Starbucks Corporation	Travel & Leisure	Public	6
Station Casinos LLC	Media	Private	1
Stryker Corporation	Health Care	Public	11
Synchrony Financial	Banks	Public	4
Target Corporation	Retail	Public	1
Texas Instruments Incorporated	Technology	Public	3
The Goldman Sachs Group, Inc.	Financial Services	Public	18
The Procter & Gamble Company	Personal & Household Goods	Public	4
The Progressive Corporation	Insurance	Public	4
The Sherwin-Williams Company	Chemicals	Public	3
United Airlines, Inc.	Industrial Goods & Services	Private	2
VMware, Inc.	Technology	Public	1
Valero Energy Corporation	Oil & Gas	Public	7
Whole Foods Market, Inc.	Retail	Private	1

Tables short horizon return

Average Abnormal Return (AAR)

Mean-adjusted model

Table A.7. Wilcoxon signed-rank test event day -4 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	79	4200	3277.500
Negative	35	2355	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: abnormal_r_MAM = 0
z = 2.608

Prob >	z	=	0.0091

Exact prob = 0.0088

Table A.8. Wilcoxon signed-rank test event day -3 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	122	13865	11183
Negative	89	8501	11183
Zero	0	0	0
All	211	22366	22366

Unadjusted variance 788401.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 788401.50

H0: abnormal_r_MAM = 0
z = 3.021

Prob >	z	=	0.0025

Table. A.9. Wilcoxon signed-rank test event day -2 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	80	8392	10050
Negative	120	11708	10050
Zero	0	0	0
All	200	20100	20100

Unadjusted variance 671675.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 671675.00

H0: abnormal_r_MAM = 0
z = -2.023

Prob >	z	=	0.0431

Exact prob = 0.0430

Table A.10. Wilcoxon signed-rank test event day -1 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	70	6574	9751.500
Negative	127	12929	9751.500
Zero	0	0	0
All	197	19503	19503

Unadjusted variance 641973.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 641973.75

H0: abnormal_r_MAM = 0
z = -3.966

Prob >	z	=	0.0001

Exact prob = 0.0001

Table A.11. Wilcoxon signed-rank test event day 0 (announcement day) for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	189	29087	26814
Negative	138	24541	26814

Zero	0	0	0
All	327	53628	53628

Unadjusted variance 2927195.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 2927195.00

H0: abnormal_r_MAM = 0
z = 1.329

Prob >	z	=	0.1840

Table A.12. Wilcoxon signed-rank test event day +1 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	163	25555	26487.500
Negative	162	27420	26487.500
Zero	0	0	0
All	325	52975	52975

Unadjusted variance 2873893.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 2873893.75

H0: abnormal_r_MAM = 0
z = -0.550

Prob >	z	=	0.5823

Table A.13. Wilcoxon signed-rank test event day +2 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	79	5147	5148
Negative	64	5149	5148
Zero	0	0	0
All	143	10296	10296

Unadjusted variance 246246.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 246246.00

H0: abnormal_r_MAM = 0
z = -0.002

Prob >	z	=	0.9984

Exact prob = 0.9992

Table A.14. Wilcoxon signed-rank test event day +3 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	72	4174	3451.500
Negative	45	2729	3451.500
Zero	0	0	0
All	117	6903	6903

Unadjusted variance 135183.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 135183.75

H0: abnormal_r_MAM = 0
z = 1.965

Prob >	z	=	0.0494

Exact prob = 0.0493

Table A.15. Wilcoxon signed-rank test event day +4 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	92	9561	10251.500
Negative	110	10942	10251.500
Zero	0	0	0
All	202	20503	20503

Unadjusted variance 691976.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 691976.25

H0: abnormal_r_MAM = 0
z = -0.830

Prob >	z	=	0.4065

Multifactor model

Table A.16. Wilcoxon signed-rank test event day -4 for multifactor model

Sign	Obs	Sum ranks	Expected

Positive	95	5168	3277.500
Negative	19	1387	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: abnormal_r_MFM = 0
z = 5.345

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.17. Wilcoxon signed-rank test event day -3 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	158	17795	11183
Negative	53	4571	11183
Zero	0	0	0
All	211	22366	22366

Unadjusted variance 788401.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 788401.50

H0: abnormal_r_MFM = 0
z = 7.447

Prob >	z	=	0.0000

Table A.18. Wilcoxon signed-rank test event day -2 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	131	13079	10050
Negative	69	7021	10050
Zero	0	0	0
All	200	20100	20100

Unadjusted variance 671675.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 671675.00

H0: abnormal_r_MFM = 0
z = 3.696

Prob >	z	=	0.0002

Exact prob = 0.0002

Table A.19. Wilcoxon signed-rank test event day -1 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	135	14095	9751.500
Negative	62	5408	9751.500
Zero	0	0	0
All	197	19503	19503

Unadjusted variance 641973.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 641973.75

H0: abnormal_r_MFM = 0
z = 5.421

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.20. Wilcoxon signed-rank test event day 0 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	245	41299	26814
Negative	82	12329	26814
Zero	0	0	0
All	327	53628	53628

Unadjusted variance 2927195.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 2927195.00

H0: abnormal_r_MFM = 0
z = 8.466

Prob >	z	=	0.0000

Table A.21. Wilcoxon signed-rank test event day +1 for multifactor model

Sign	Obs	Sum ranks	Expected

Positive	255	42776	26487.500
Negative	70	10199	26487.500
Zero	0	0	0
All	325	52975	52975

Unadjusted variance 2873893.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 2873893.75

H0: abnormal_r_MFM = 0
z = 9.608

Prob >	z	=	0.0000

Table A.22. Wilcoxon signed-rank test event day +2 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	103	7558	5148
Negative	40	2738	5148
Zero	0	0	0
All	143	10296	10296

Unadjusted variance 246246.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 246246.00

H0: abnormal_r_MFM = 0
z = 4.857

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.23. Wilcoxon signed-rank test event day +3 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	95	5781	3451.500
Negative	22	1122	3451.500
Zero	0	0	0
All	117	6903	6903

Unadjusted variance 135183.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 135183.75

H0: abnormal_r_MFM = 0
z = 6.336

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.24. Wilcoxon signed-rank test event day +4 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	127	14023	10251.500
Negative	75	6480	10251.500
Zero	0	0	0
All	202	20503	20503

Unadjusted variance 691976.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 691976.25

H0: abnormal_r_MFM = 0
z = 4.534

Prob >	z	=	0.0000

Matching portfolio industry

Table A.25. Wilcoxon signed-rank test event day -4 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	81	4863	3277.500
Negative	33	1692	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: abnormal_r_MPI = 0

z = 4.483

Prob >	z	=	0.0000

Table A.26. Wilcoxon signed-rank test event day -3 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	145	16209	11183
Negative	66	6157	11183
Zero	0	0	0
All	211	22366	22366

Unadjusted variance	788401.50
Adjustment for ties	0.00
Adjustment for zeros	0.00

Adjusted variance 788401.50

H0: abnormal_r_MPI = 0

z = 5.660

Prob >	z	=	0.0000

Table A.27. Wilcoxon signed-rank test event day -2 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	109	10346	10050
Negative	91	9754	10050
Zero	0	0	0

All	200	20100	20100

Unadjusted	variance		671675.00
Adjustment	for	ties	0.00
Adjustment	for	zeros	0.00

Adjusted variance 671675.00

H0: abnormal_r_MPI = 0

z = 0.361

Prob >	z	=	0.7180

Table A.28. Wilcoxon signed-rank test event day -1 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	121	11511	9751.500
Negative	76	7992	9751.500
Zero	0	0	0
All	197	19503	19503

Unadjusted	variance		641973.75
Adjustment	for	ties	0.00
Adjustment	for	zeros	0.00

Adjusted variance 641973.75

H0: abnormal_r_MPI = 0

z = 2.196

Prob >	z	=	0.0281

Table A.29. Wilcoxon signed-rank test event day 0 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	218	34789	26814

Negative	109	18839	26814
Zero	0	0	0
All	327	53628	53628

Unadjusted variance	2927195.00
Adjustment for ties	0.00
Adjustment for zeros	0.00

Adjusted variance 2927195.00

H0: abnormal_r_MPI = 0

z = 4.661

Prob > z = 0.0000

Table A.30. Wilcoxon signed-rank test event day +1 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	222	36625	26487.500
Negative	103	16350	26487.500
Zero	0	0	0
All	325	52975	52975

Unadjusted variance	2873893.75
Adjustment for ties	0.00
Adjustment for zeros	0.00

Adjusted variance 2873893.75

H0: abnormal_r_MPI = 0

z = 5.980

Prob > z = 0.0000

Table A.31. Wilcoxon signed-rank test event day +2 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	100	7035	5148
Negative	43	3261	5148
Zero	0	0	0
All	143	10296	10296

Unadjusted variance	246246.00
Adjustment for ties	0.00
Adjustment for zeros	0.00

Adjusted variance 246246.00

H0: abnormal_r_MPI = 0

z = 3.803

Prob > z = 0.0001

Table A.32. Wilcoxon signed-rank test event day +3 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	85	5056	3451.500
Negative	32	1847	3451.500
Zero	0	0	0
All	117	6903	6903

Unadjusted variance	135183.75
Adjustment for ties	0.00
Adjustment for zeros	0.00

Adjusted variance 135183.75

H0: abnormal_r_MPI = 0

z = 4.364

Prob >	z	=	0.0000

Table A.33. Wilcoxon signed-rank test event day +4 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	136	14374	10251.500
Negative	66	6129	10251.500
Zero	0	0	0
All	202	20503	20503

Unadjusted variance	691976.25
Adjustment for ties	0.00
Adjustment for zeros	0.00

Adjusted variance 691976.25

H0: abnormal_r_MPI = 0

z = 4.956

Prob >	z	=	0.0000

Matching portfolio rating

Table A.34. Wilcoxon signed-rank test event day -4 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	89	4935	3277.500
Negative	25	1620	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: abnormal_r_MPR = 0
z = 4.686

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.35. Wilcoxon signed-rank test event day -3 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	144	16195	11183
Negative	67	6171	11183
Zero	0	0	0
All	211	22366	22366

Unadjusted variance 788401.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 788401.50

H0: abnormal_r_MPR = 0
z = 5.645

Prob >	z	=	0.0000

Table A.36. Wilcoxon signed-rank test event day -2 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	99	9989	10050
Negative	101	10111	10050
Zero	0	0	0
All	200	20100	20100

Unadjusted variance 671675.00
Adjustment for ties -0.13
Adjustment for zeros 0.00

Adjusted variance 671674.88

H0: abnormal_r_MPR = 0
z = -0.074

Prob >	z	=	0.9407

Exact prob = 0.9410

Table A.37. Wilcoxon signed-rank test event day -1 for matching portfolio rating

Sign	Obs	Sum	ranks	Expected
Positive	119	11021		9751.500
Negative	78	8482		9751.500
Zero	0	0		0
All	197	19503		19503

Unadjusted variance 641973.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 641973.75

H0: abnormal_r_MPR = 0
z = 1.584

Prob >	z	=	0.1131

Exact prob = 0.1134

Table A.38. Wilcoxon signed-rank test event day 0 (announcement day) for matching portfolio rating

Sign	Obs	Sum	ranks	Expected
Positive	229	36705		26814
Negative	98	16923		26814
Zero	0	0		0
All	327	53628		53628

Unadjusted variance 2927195.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 2927195.00

H0: abnormal_r_MPR = 0
z = 5.781

Prob >	z	=	0.0000

Table A.39. Wilcoxon signed-rank test event day 1 for matching portfolio rating

Sign	Obs	Sum	ranks	Expected
Positive	230	36800		26487.500
Negative	95	16175		26487.500
Zero	0	0		0
All	325	52975		52975

Unadjusted variance 2873893.75
Adjustment for ties -0.13
Adjustment for zeros 0.00

Adjusted variance 2873893.63

H0: abnormal_r_MPR = 0
z = 6.083

Prob >	z	=	0.0000

Table A.40. Wilcoxon signed-rank test event day 2 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	97	7215	5148
Negative	46	3081	5148
Zero	0	0	0
All	143	10296	10296

Unadjusted variance 246246.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 246246.00

H0: abnormal_r_MPR = 0
z = 4.165

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.41. Wilcoxon signed-rank test event day 3 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	83	5009	3451.500
Negative	34	1894	3451.500
Zero	0	0	0
All	117	6903	6903

Unadjusted variance 135183.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 135183.75

H0: abnormal_r_MPR = 0
z = 4.236

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.42. Wilcoxon signed-rank test event day 4 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	129	14096	10251.500

Negative	73	6407	10251.500
Zero	0	0	0
All	202	20503	20503

Unadjusted variance 691976.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 691976.25

H0: abnormal_r_MPR = 0
z = 4.622

Prob >	z	=	0.0000

Cumulative Average Abnormal Return (CAAR)

Mean-adjusted model

Table A.43. Wilcoxon signed-rank test event day -4 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	79	4200	3277.500
Negative	35	2355	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: CAR_MAM_B4 = 0
z = 2.608

Prob >	z	=	0.0091

Exact prob = 0.0088

Table A.44. Wilcoxon signed-rank test event day -3 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	163	20158	15438
Negative	85	10718	15438
Zero	0	0	0

All	248	30876	30876

Unadjusted variance 1278781.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 1278781.00

H0: CAR_MAM_B3 = 0
z = 4.174

Prob >	z	=	0.0000

Table A.45. Wilcoxon signed-rank test event day -2 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	196	31558	28308
Negative	140	25058	28308
Zero	0	0	0
All	336	56616	56616

Unadjusted variance 3175214.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3175214.00

H0: CAR_MAM_B2 = 0
z = 1.824

Prob >	z	=	0.0682

Table A.46. Wilcoxon signed-rank test event day -1 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	178	27519	28985
Negative	162	30451	28985
Zero	0	0	0
All	340	57970	57970

Unadjusted variance 3289797.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3289797.50

H0: CAR_MAM_B1 = 0
z = -0.808

Prob >	z	=	0.4189

Note: Exact p-value is not computed by default for sample sizes > 200.
Use option exact to compute it.

Table A.47. Wilcoxon signed-rank test event day 0 (Announcement day) for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	192	30313	30712.500
Negative	158	31112	30712.500
Zero	0	0	0
All	350	61425	61425

Unadjusted variance 3588243.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3588243.75

H0: CAR_MAM_0 = 0
z = -0.211

Prob >	z	=	0.8330

Table A.48. Wilcoxon signed-rank test event day +1 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	191	30194	30888
Negative	160	31582	30888
Zero	0	0	0
All	351	61776	61776

Unadjusted variance 3619044.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3619044.00

H0: CAR_MAM_A1 = 0
z = -0.365

Prob >	z	=	0.7153

Table A.49. Wilcoxon signed-rank test event day +2 for mean-adjusted model

Sign	Obs	Sum ranks	Expected

Positive	187	29481	31064
Negative	165	32647	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MAM_A2 = 0
z = -0.829

Prob >	z	=	0.4073

Table A.50. Wilcoxon signed-rank test event day +3 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	188	30040	31064
Negative	164	32088	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MAM_A3 = 0
z = -0.536

Prob >	z	=	0.5920

Table A.51. Wilcoxon signed-rank test event day +4 for mean-adjusted model

Sign	Obs	Sum ranks	Expected
Positive	178	28655	31240.500
Negative	175	33826	31240.500
Zero	0	0	0
All	353	62481	62481

Unadjusted variance 3681172.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3681172.25

H0: CAR_MAM_A4 = 0
z = -1.348

Prob >	z	=	0.1778

Multifactor model

Table A.52. Wilcoxon signed-rank test event day -4 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	95	5168	3277.500
Negative	19	1387	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: CAR_MFM_B4 = 0
z = 5.345

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.53. Wilcoxon signed-rank test event day -3 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	195	25454	15438
Negative	53	5422	15438
Zero	0	0	0
All	248	30876	30876

Unadjusted variance 1278781.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 1278781.00

H0: CAR_MFM_B3 = 0
z = 8.857

Prob >	z	=	0.0000

Table A.54. Wilcoxon signed-rank test event day -2 for multifactor model

Sign	Obs	Sum	ranks	Expected
Positive	254	44542	28308	
Negative	82	12074	28308	
Zero	0	0	0	
All	336	56616	56616	

Unadjusted variance 3175214.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3175214.00

H0: CAR_MFM_B2 = 0
z = 9.110

Prob >	z	=	0.0000

Table A.55. Wilcoxon signed-rank test event day -1 for multifactor model

Sign	Obs	Sum	ranks	Expected
Positive	260	46496	28985	
Negative	80	11474	28985	
Zero	0	0	0	
All	340	57970	57970	

Unadjusted variance 3289797.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3289797.50

H0: CAR_MFM_B1 = 0
z = 9.654

Prob >	z	=	0.0000

Table A.56. Wilcoxon signed-rank test event day 0 (announcement day) for multifactor model

Sign	Obs	Sum	ranks	Expected
Positive	273	50460	30712.500	

Negative	77	10965	30712.500
Zero	0	0	0
All	350	61425	61425

Unadjusted variance 3588243.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3588243.75

H0: CAR_MFM_0 = 0
z = 10.425

Prob >	z	=	0.0000

Table A.57. Wilcoxon signed-rank test event day +1 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	282	52327	30888
Negative	69	9449	30888
Zero	0	0	0
All	351	61776	61776

Unadjusted variance 3619044.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3619044.00

H0: CAR_MFM_A1 = 0
z = 11.270

Prob >	z	=	0.0000

Table A.58. Wilcoxon signed-rank test event day +2 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	279	53084	31064
Negative	73	9044	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MFM_A2 = 0			
z = 11.526			
Prob >	z	=	0.0000

Table A.59. Wilcoxon signed-rank test event day +3 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	282	53892	31064
Negative	70	8236	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MFM_A3 = 0			
z = 11.949			
Prob >	z	=	0.0000

Table A.60. Wilcoxon signed-rank test event day +4 for multifactor model

Sign	Obs	Sum ranks	Expected
Positive	288	55265	31240.500
Negative	65	7216	31240.500
Zero	0	0	0
All	353	62481	62481

Unadjusted variance 3681172.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3681172.25

H0: CAR_MFM_A4 = 0			
z = 12.522			
Prob >	z	=	0.0000

Matching portfolio industry

Table A.61. Wilcoxon signed-rank test event day -4 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	81	4863	3277.500
Negative	33	1692	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: CAR_MPI_B4 = 0
z = 4.483

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.62. Wilcoxon signed-rank test event day -3 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	178	23232	15438
Negative	70	7644	15438
Zero	0	0	0
All	248	30876	30876

Unadjusted variance 1278781.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 1278781.00

H0: CAR_MPI_B3 = 0
z = 6.892

Prob >	z	=	0.0000

Table A.63. Wilcoxon signed-rank test event day -2 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	228	36931	28308
Negative	108	19685	28308
Zero	0	0	0
All	336	56616	56616

Unadjusted variance 3175214.00

Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3175214.00

H0: CAR_MPI_B2 = 0
z = 4.839

Prob >	z	=	0.0000

Table A.64. Wilcoxon signed-rank test event day -1 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	229	37934	28985
Negative	111	20036	28985
Zero	0	0	0
All	340	57970	57970

Unadjusted variance 3289797.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3289797.50

H0: CAR_MPI_B1 = 0
z = 4.934

Prob >	z	=	0.0000

Table A.65. Wilcoxon signed-rank test event day 0 (Announcement day) for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	250	42334	30712.500
Negative	100	19091	30712.500
Zero	0	0	0
All	350	61425	61425

Unadjusted variance 3588243.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3588243.75

H0: CAR_MPI_0 = 0
z = 6.135

Prob >	z	=	0.0000

Table A.66. Wilcoxon signed-rank test event day 1 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	248	44122	30888
Negative	103	17654	30888
Zero	0	0	0
All	351	61776	61776

Unadjusted variance 3619044.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3619044.00

H0: CAR_MPI_A1 = 0
z = 6.957
Prob > z = 0.0000

Table A.67. Wilcoxon signed-rank test event day 2 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	247	44625	31064
Negative	105	17503	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MPI_A2 = 0
z = 7.098
Prob > z = 0.0000

Table A.68. Wilcoxon signed-rank test event day 3 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	247	44842	31064
Negative	105	17286	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MPI_A3 = 0
z = 7.212

Prob >	z	=	0.0000

Table A.69. Wilcoxon signed-rank test event day 4 for matching portfolio industry

Sign	Obs	Sum ranks	Expected
Positive	262	47633	31240.500
Negative	91	14848	31240.500
Zero	0	0	0
All	353	62481	62481

Unadjusted variance 3681172.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3681172.25

H0: CAR_MPI_A4 = 0
z = 8.544

Prob >	z	=	0.0000

Matching portfolio rating

Table A.70. Wilcoxon signed-rank test event day -4 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	89	4935	3277.500
Negative	25	1620	3277.500
Zero	0	0	0
All	114	6555	6555

Unadjusted variance 125091.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 125091.25

H0: CAR_MPR_B4 = 0
z = 4.686

Prob >	z	=	0.0000

Exact prob = 0.0000

Table A.71. Wilcoxon signed-rank test event day -3 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	184	23480	15438
Negative	64	7396	15438
Zero	0	0	0
All	248	30876	30876

Unadjusted variance 1278781.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 1278781.00

H0: CAR_MPR_B3 = 0
z = 7.112

Prob >	z	=	0.0000

Table A.72. Wilcoxon signed-rank test event day -2 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	227	36259	28308
Negative	109	20357	28308
Zero	0	0	0
All	336	56616	56616

Unadjusted variance 3175214.00
Adjustment for ties -0.13
Adjustment for zeros 0.00

Adjusted variance 3175213.88

H0: CAR_MPR_B2 = 0
z = 4.462

Prob >	z	=	0.0000

Table A.73. Wilcoxon signed-rank test event day -1 for matching portfolio rating

Sign	Obs	Sum	ranks	Expected
Positive	228	36773	28985	
Negative	112	21197	28985	
Zero	0	0	0	
All	340	57970	57970	

Unadjusted variance 3289797.50
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3289797.50

H0: CAR_MPR_B1 = 0
z = 4.294

Prob >	z	=	0.0000

Table A.74. Wilcoxon signed-rank test event day 0 (Announcement day) for matching portfolio rating

Sign	Obs	Sum	ranks	Expected
Positive	240	42067	30712.500	
Negative	110	19358	30712.500	
Zero	0	0	0	
All	350	61425	61425	

Unadjusted variance 3588243.75
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3588243.75

H0: CAR_MPR_0 = 0
z = 5.994

Prob >	z	=	0.0000

Table A.75. Wilcoxon signed-rank test event day 1 for matching portfolio rating

Sign	Obs	Sum	ranks	Expected
Positive	244	43953	30888	
Negative	107	17823	30888	
Zero	0	0	0	
All	351	61776	61776	

Unadjusted variance 3619044.00

Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3619044.00

H0: CAR_MPR_A1 = 0
z = 6.868

Prob >	z	=	0.0000

Table A76. Wilcoxon signed-rank test event day 2 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	242	44793	31064
Negative	110	17335	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MPR_A2 = 0
z = 7.186

Prob >	z	=	0.0000

Table A.77. Wilcoxon signed-rank test event day 3 for matching portfolio rating

Sign	Obs	Sum ranks	Expected
Positive	239	45101	31064
Negative	113	17027	31064
Zero	0	0	0
All	352	62128	62128

Unadjusted variance 3650020.00
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3650020.00

H0: CAR_MPR_A3 = 0
z = 7.347

Prob >	z	=	0.0000

Table A.78. Wilcoxon signed-rank test for event day 4 for matching portfolio rating

Sign	Obs	Sum ranks	Expected

Positive	257	48292	31240.500
Negative	96	14189	31240.500
Zero	0	0	0
All	353	62481	62481

Unadjusted variance 3681172.25
Adjustment for ties 0.00
Adjustment for zeros 0.00

Adjusted variance 3681172.25

H0: CAR_MPR_A4 = 0
z = 8.887

Prob >	z	=	0.0000

Tables cross-sectional tests

Average abnormal aeturn (AAR)

Mean-adjusted model

Table A.79. Regression output Average Abnormal Return (AAR) for the mean adjusted model.

	Mean-adjusted model								
Variables \ Event day	(-4)	(-3)	(-2)	(-1)	(0)	(+1)	(+2)	(+3)	(+4)
SIZE (ln)	-0.00046	-0.00005	-0.00132	0.00020	-0.00055	0.00003	-0.00063	0.00040	-0.00006
	(0.80)	(0.13)	(2.04)**	(0.52)	(1.32)	(0.07)	(0.90)	(0.56)	(0.07)
ROA	0.00004	-0.00008	0.00020	0.00002	0.00008	0.00004	0.00001	-0.00002	-0.00022
	(0.26)	(0.88)	(1.25)	(0.24)	(0.83)	(0.46)	(0.06)	(0.15)	(1.92)*
LEV	-0.00147	0.00009	0.00534	-0.00122	0.00327	-0.00024	-0.00035	0.00036	0.00266
	(0.45)	(0.05)	(1.28)	(0.61)	(1.53)	(0.12)	(0.10)	(0.10)	(1.45)
INT_COV	-0.00000	-0.00000	0.00000	-0.00000	0.00000	0.00000	-0.00000	0.00000	0.00000
	(0.18)	(1.22)	(0.18)	(1.47)	(0.28)	(1.79)*	(0.07)	(0.88)	(0.11)
INTANG	0.00172	0.00035	0.00339	-0.00154	-0.00038	0.00009	0.00070	0.00301	0.00291
	(1.03)	(0.24)	(0.92)	(0.78)	(0.20)	(0.06)	(0.29)	(1.27)	(1.31)
NIG	-0.00466	0.00078	-0.00495	0.00075	-0.00058	-0.00040	0.00148	0.00274	0.00225
	(1.92)*	(0.38)	(2.20)**	(1.16)	(0.32)	(0.34)	(0.68)	(0.94)	(1.32)
CONSTANT	0.01152	0.00242	0.02474	-0.00535	0.01046	-0.00099	0.01448	-0.00998	-0.00008
	(0.23)	(0.34)	(2.00)*	(0.84)	(1.42)	(0.64)	(1.03)	(0.41)	(0.12)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2-adjusted	0.22	0.11	0.12	0.11	0.14	0.12	-0.05	0.22	0.17
N	114	211	200	197	327	325	143	117	202

* p<0.1; ** p<0.05; *** p<0.01

Multifactor model

Table A.80. Regression output Average Abnormal Return (AAR) for the multifactor model.

	Multifactor model								
Variables \ Event day	(-4)	(-3)	(-2)	(-1)	(0)	(+1)	(+2)	(+3)	(+4)
SIZE (ln)	-0.00026	-0.00038	-0.00026	-0.00025	-0.00034	-0.00044	-0.00004	0.00010	-0.00062
	(0.91)	(2.68)***	(1.32)	(1.21)	(2.22)**	(2.84)***	(0.25)	(0.32)	(3.37)***
ROA	-0.00013	0.00003	0.00001	-0.00000	0.00002	0.00000	0.00000	-0.00000	-0.00006
	(1.82)*	(0.73)	(0.13)	(0.04)	(0.45)	(0.04)	(0.08)	(0.00)	(1.78)*
LEV	-0.00328	0.00051	0.00019	0.00116	0.00159	0.00137	0.00119	-0.00280	0.00070
	(1.50)	(0.81)	(0.30)	(1.74)*	(2.18)**	(1.71)*	(0.92)	(1.73)*	(1.24)
INT_COV	-0.00000	-0.00000	0.00000	0.00000	-0.00000	-0.00000	0.00000	-0.00000	-0.00000
	(1.18)	(1.43)	(0.23)	(0.06)	(0.71)	(0.72)	(0.79)	(0.11)	(0.52)
INTANG	-0.00040	-0.00120	-0.00133	-0.00089	-0.00084	-0.00122	0.00015	-0.00059	0.00013
	(0.40)	(1.85)*	(1.29)	(0.87)	(1.47)	(1.33)	(0.16)	(0.51)	(0.18)
NIG	0.00110	-0.00148	0.00092	-0.00035	-0.00035	-0.00020	0.00101	0.00190	-0.00096
	(0.80)	(2.05)**	(1.43)	(0.44)	(0.77)	(0.49)	(0.52)	(0.96)	(1.40)
CONSTANT	0.01081	0.01023	0.00659	0.00637	0.00848	0.01124	0.00078	0.00240	0.01544
	(1.17)	(1.78)*	(1.11)	(0.77)	(1.43)	(2.54)**	(0.53)	(1.40)	(2.28)**
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2-adjusted	0.37	0.39	0.20	0.31	0.19	0.25	0.48	0.38	0.33
N	114	211	200	197	327	325	143	117	202

* p<0.1; ** p<0.05; *** p<0.01

Matching portfolio industry

Table A.81. Regression output Average Abnormal Return (AAR) for the matching portfolio industry.

	Matching portfolio industry								
Variables \ Event day	(-4)	(-3)	(-2)	(-1)	(0)	(+1)	(+2)	(+3)	(+4)
SIZE (ln)	-0.00105	-0.00038	-0.00170	0.00003	-0.00085	-0.00026	-0.00091	-0.00006	-0.00040
	(1.71)*	(1.11)	(2.41)**	(0.09)	(1.91)*	(0.58)	(1.24)	(0.09)	(0.52)
ROA	-0.00002	-0.00008	0.00017	-0.00000	0.00006	0.00002	-0.00006	-0.00007	-0.00021
	(0.13)	(0.86)	(1.00)	(0.05)	(0.58)	(0.23)	(0.33)	(0.55)	(1.74)*
LEV	-0.00342	0.00163	0.00657	-0.00064	0.00336	0.00003	-0.00117	-0.00007	0.00273
	(1.08)	(0.82)	(1.45)	(0.36)	(1.45)	(0.01)	(0.33)	(0.03)	(1.43)
INT_COV	0.00000	-0.00000	-0.00000	-0.00000	0.00000	0.00000	-0.00000	0.00000	-0.00000
	(0.16)	(2.03)**	(0.37)	(1.31)	(0.67)	(1.00)	(0.70)	(0.77)	(0.09)
INTANG	0.00226	-0.00129	0.00208	-0.00200	0.00015	0.00009	0.00112	0.00263	0.00143
	(1.18)	(0.89)	(0.51)	(0.86)	(0.08)	(0.06)	(0.35)	(1.28)	(0.64)
NIG	-0.00634	0.00086	-0.00450	0.00130	-0.00089	-0.00058	0.00081	0.00132	0.00193
	(2.00)*	(0.42)	(1.68)	(1.89)*	(0.42)	(0.48)	(0.40)	(0.56)	(1.17)
CONSTANT	0.02872	0.01028	0.03426	-0.00000	0.01892	0.00737	0.02399	0.00326	0.01060
	(1.10)	(1.25)	(2.26)**	(0.66)	(1.81)*	(0.85)	(1.29)	(0.05)	(0.29)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2-adjusted	0.19	0.09	0.09	0.25	0.19	0.18	0.14	0.07	0.26
N	114	211	200	197	327	325	143	117	202

* p<0.1; ** p<0.05; *** p<0.01

Matching portfolio rating

Table A.82. Regression output Average Abnormal Return (AAR) for the matching portfolio rating.

Variables \ Event day	(-4)	(-3)	(-2)	(-1)	(0)	(+1)	(+2)	(+3)	(+4)
	Matching portfolio rating								
SIZE (ln)	-0.00081	-0.00040	-0.00171	-0.00003	-0.00083	-0.00027	-0.00073	-0.00005	-0.00036
	(1.43)	(1.08)	(2.64)**	(0.09)	(1.93)*	(0.59)	(0.89)	(0.07)	(0.49)
ROA	-0.00000	-0.00007	0.00017	-0.00002	0.00007	0.00003	-0.00001	-0.00008	-0.00028
	(0.04)	(0.65)	(1.03)	(0.18)	(0.67)	(0.26)	(0.08)	(0.65)	(2.57)**
LEV	-0.00187	0.00084	0.00569	-0.00092	0.00391	-0.00003	-0.00063	0.00073	0.00269
	(0.63)	(0.40)	(1.39)	(0.49)	(1.81)*	(0.01)	(0.18)	(0.24)	(1.53)
INT_COV	-0.00000	-0.00000	0.00000	-0.00000	-0.00000	0.00000	-0.00000	0.00000	-0.00000
	(0.64)	(1.42)	(0.17)	(1.52)	(0.09)	(1.14)	(0.33)	(0.55)	(0.58)
INTANG	0.00131	0.00012	0.00357	-0.00160	-0.00022	-0.00036	0.00071	0.00215	0.00179
	(0.68)	(0.08)	(0.94)	(0.68)	(0.11)	(0.23)	(0.22)	(1.02)	(0.91)
NIG	-0.00439	0.00278	-0.00390	0.00173	0.00064	-0.00009	0.00179	0.00050	-0.00059
	(1.97)*	(1.13)	(1.49)	(2.01)*	(0.32)	(0.06)	(0.47)	(0.18)	(0.36)
CONSTANT	0.02175	0.01088	0.03428	0.00159	0.01835	0.00767	0.01993	0.00277	0.01070
	(0.87)	(1.52)	(2.64)**	(0.87)	(1.90)*	(0.85)	(1.07)	(0.07)	(0.30)
Year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2-adjusted	0.20	0.12	0.07	0.22	0.18	0.19	0.20	0.14	0.33
N	114	211	200	197	327	325	143	117	202

* p<0.1; ** p<0.05; *** p<0.01

Tables robustness checks

Cumulative Abnormal Return

Table A.83. Regression results for Cumulative Abnormal Return (CAR) during the event window (-4, 4) for all benchmark models with firm-level and bond-level controls. Definitions for all control variables are available in section 4.4.4.

	CAR MAM	**CAR MFM**	**CAR MPI**	**CAR MPR**
NIG	-0.00198	0.00044	-0.00209	0.00118
	(0.43)	(0.25)	(0.42)	(0.20)
SIZE (ln)	-0.00147	-0.00105	-0.00264	-0.00253
	(1.73)*	(2.53)**	(3.11)***	(2.93)***
ROA	0.00001	-0.00007	-0.00010	-0.00012
	(0.04)	(0.67)	(0.49)	(0.55)
LEV	0.00718	0.00453	0.00946	0.01024
	(1.45)	(2.65)***	(2.36)**	(2.20)**
INT_COV	-0.00000	-0.00000	-0.00000	-0.00000
	(0.51)	(1.92)*	(1.25)	(1.27)
INTANG	0.00593	-0.00420	0.00348	0.00430
	(1.53)	(2.02)**	(0.94)	(1.16)
COV	-0.00168	-0.00362	-0.00312	-0.00225
	(0.53)	(1.57)	(0.95)	(0.61)
END_MAT	0.00453	-0.00284	0.00368	0.00299
	(1.46)	(1.03)	(0.87)	(0.63)
IPO	0.00649	-0.00282	0.00382	0.00251
	(1.89)*	(1.17)	(0.99)	(0.61)
CONSTANT	0.02844	0.03347	0.06511	0.06164
	(1.65)	(1.32)	(1.83)*	(1.96)*
Year fixed effects	Yes	Yes	Yes	Yes
R^2 -adjusted	0.10	0.27	0.15	0.14
N	353	353	353	353

* p<0.1; ** p<0.05; *** p<0.01

Note: Standard errors are clustered on firm. t-value is reported in parenthesis. The t-statistics that is reported is based on the standardized cumulative abnormal return (SCAR) and the sign and magnitude is based on unstandardized cumulative abnormal return (CAR). (ln) indicates that the variable has been transformed by the natural logarithm.

Table A.84. Regression results for Cumulative Abnormal Return (CAR) during the event window (-4, 4) for all benchmark models and firm-level controls including LOSS. Definitions for all control variables are available in section 4.4.4.

	CAR MAM	**CAR MFM**	**CAR MPI**	**CAR MPR**
NIG	-0.00225	0.00047	-0.00227	0.00079
	(0.52)	(0.26)	(0.45)	(0.14)
SIZE (ln)	-0.00131	-0.00107	-0.00250	-0.00234
	(1.54)	(2.65)***	(2.93)***	(2.66)***
ROA	0.00009	-0.00010	-0.00005	-0.00002
	(0.43)	(0.89)	(0.21)	(0.07)
LEV	0.00869	0.00438	0.01069	0.01167
	(1.67)*	(2.42)**	(2.50)**	(2.31)**
INT_COV	0.00000	-0.00000	-0.00000	-0.00000
	(0.30)	(1.45)	(0.63)	(0.92)
INTANG	0.00610	-0.00486	0.00336	0.00430
	(1.56)	(2.44)**	(0.89)	(1.15)
LOSS	0.01249	-0.00305	0.00898	0.01498
	(0.78)	(1.48)	(0.78)	(0.83)
CONSTANT	0.02204	0.03079	0.05798	0.05357
	(1.55)	(1.27)	(1.71)*	(1.84)*
Year fixed effects	Yes	Yes	Yes	Yes
R^2 -adjusted	0.11	0.27	0.16	0.16
N	353	353	353	353

* *p*<0.1; ** *p*<0.05; *** *p*<0.01

Table A.85. Regression results for Cumulative Abnormal Return (CAR) during the event window (-4, 4) for all benchmark models and firm-level, bond-level and list level controls. Definitions for all control variables are available in section 4.4.4.

	CAR MAM	CAR MFM	CAR MPR	CAR MPR
NIG	-0.00232	0.00073	0.00090	0.00090
	(0.48)	(0.43)	(0.14)	(0.14)
SIZE (ln)	-0.00172	-0.00102	-0.00275	-0.00275
	(1.89)*	(2.45)**	(2.98)***	(2.98)***
ROA	-0.00000	-0.00006	-0.00013	-0.00013
	(0.01)	(0.56)	(0.58)	(0.58)
LEV	0.00810	0.00387	0.01100	0.01100
	(1.56)	(2.21)**	(2.26)**	(2.26)**
INT_COV	-0.00000	-0.00000	-0.00000	-0.00000
	(0.69)	(1.95)*	(1.39)	(1.39)
INTANG	0.00602	-0.00417	0.00438	0.00438
	(1.51)	(1.96)*	(1.13)	(1.13)
COV	-0.00160	-0.00401	-0.00220	-0.00220
	(0.51)	(1.71)*	(0.60)	(0.60)
END_MAT	0.00524	-0.00317	0.00359	0.00359
	(1.64)	(1.16)	(0.74)	(0.74)
IPO	0.00674	-0.00222	0.00276	0.00276
	(1.95)*	(0.85)	(0.63)	(0.63)
FIRST	-0.00016	-0.00223	-0.00025	-0.00025
	(0.07)	(1.57)	(0.10)	(0.10)
TOP25	0.00281	-0.00120	0.00237	0.00237
	(1.32)	(1.42)	(1.14)	(1.14)
CONSTANT	0.03326	0.03386	0.06584	0.06584
	(1.68)*	(1.38)	(2.08)**	(2.08)**
Year fixed effects				
R^2 -adjusted	0.10	0.28	0.14	0.14
N	353	353	353	353

* p<0.1; ** p<0.05; *** p<0.01

Note: Standard errors are clustered on firm. t-value is reported in parenthesis. The t-statistics that is reported is based on the standardized cumulative abnormal return (SCAR) and the sign and magnitude is based on unstandardized cumulative abnormal return (CAR). (ln) indicates that the variable has been transformed by the natural logarithm.

Table A.86. Regression results for Cumulative Abnormal Return (CAR) during the event window (-4, 4) for all benchmark models and firm-level, bond-level and most relevant list level controls. Definitions for all control variables are available in section 4.4.4.

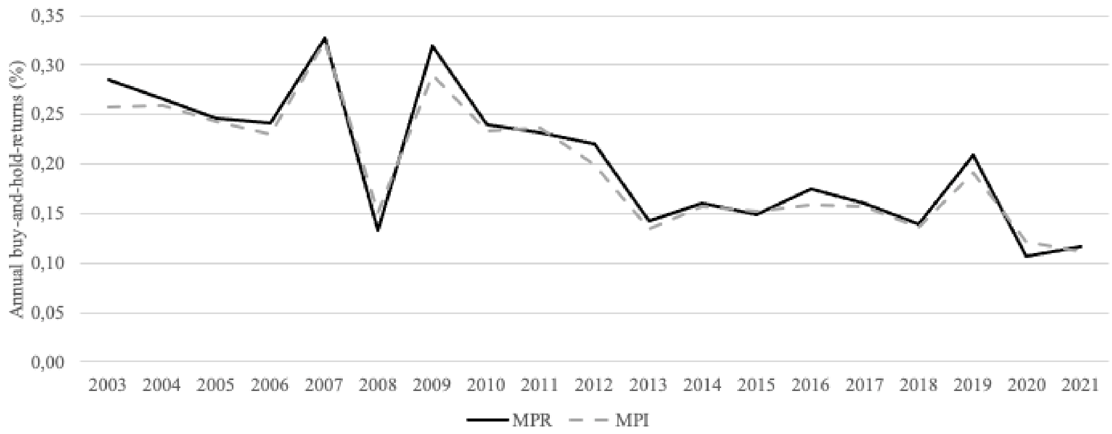
	CAR MAM	**CAR MFM**	**CAR MPI**	**CAR MPR**
SIZE	-0.00137	-0.00114	-0.00261	-0.00241
	(1.67)*	(3.32)***	(3.29)***	(2.67)***
ROA	0.00010	-0.00009	-0.00003	-0.00000
	(0.54)	(0.82)	(0.16)	(0.01)
LEV	0.00794	0.00412	0.00990	0.01121
	(1.52)	(2.42)**	(2.12)**	(2.02)**
INT_COV	-0.00000	-0.00000	-0.00000	-0.00000
	(0.39)	(1.89)*	(1.22)	(1.18)
INTAG	0.00614	-0.00418	0.00366	0.00456
	(1.90)*	(2.08)**	(1.07)	(1.27)
LOSS	0.01204	-0.00249	0.00892	0.01522
	(0.84)	(0.74)	(0.84)	(0.91)
NIG	-0.00234	0.00065	-0.00230	0.00072
	(0.51)	(0.53)	(0.56)	(0.14)
FIRST	-0.00027	-0.00212	-0.00119	-0.00023
	(0.11)	(1.55)	(0.48)	(0.09)
COV	-0.00224	-0.00384	-0.00369	-0.00294
	(0.59)	(1.69)*	(1.00)	(0.70)
END_MAT	0.00433	-0.00282	0.00352	0.00273
	(1.23)	(1.05)	(0.79)	(0.61)
IPO	0.00536	-0.00191	0.00329	0.00105
	(1.27)	(0.76)	(0.75)	(0.21)
CONSTANT	0.02556	0.03640	0.06404	0.05789
	(1.51)	(1.69)*	(1.76)*	(1.81)*
Year fixed effects	Yes	Yes	Yes	Yes
R^2 -adjusted	0.11	0.28	0.15	0.15
N	353	353	353	353

* p<0.1; ** p<0.05; *** p<0.01

Note: Standard errors are clustered on firm. t-value is reported in parenthesis. The t-statistics that is reported is based on the standardized cumulative abnormal return (SCAR) and the sign and magnitude is based on unstandardized cumulative abnormal return (CAR).

Long-run horizon

Figure A.2. Illustration of annual buy-and-hold returns



Reference list for appendices

Stock, J. H. (2020). Introduction to econometrics (Fourth edition, global edition). Pearson.