Employee Sentiment for Factor Investing in the Corporate Bond Market

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Declaration

This report is submitted as a part requirement for the degree MSc Computational Statistics and Machine Learning at UCL.

I, Daniel Stancl, hereby proclaim that I wrote this work on my own under the leadership of my supervisors and that the references include all resources and literature I have used.

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Abstract

This thesis investigates the relationship between employee sentiment, proxied by Glassdoor reviews and ratings, and future returns on bonds of corresponding companies. While sentiment analysis is well studied for probing into how companies are perceived by investors or the general public, it is a novel idea to use employee sentiment as a predictor of corporate bond performance. Although a few studies scrutinising the relationship between employee sentiment and stock returns have appeared, to the best of my knowledge, this is the first attempt to place this analysis to corporate bonds.

This research was conducted in collaboration with Fidelity International and entails a series of experiments that examine how employee satisfaction might be utilised as an indicator of returns on corporate bonds. This project was prepared as a separate piece of work, in cooperation with an ESG-oriented research group under the supervision of Prof. Philip Treleaven.

The thesis consists of the following four components - a data retrieval pipeline, two experiments and an exploratory analysis:

1. **Data Retrieval and Database Pipeline**. This work engineers a pipeline for scraping employee reviews and related information from Glassdoor using a Python's Selenium-based crawler. Subsequently, the information is stored in the database built using Django which makes it easily available for future research endeavours.

2. **Investigation of Employee Sentiment based on Ratings in Generating Return**. This experiment investigates the use of analysis of employee ratings for factor investing. Long-short and long portfolios are constructed, and their returns compared with those of the baseline counterparts.

3. **Comparison of Different Sentiment Scoring Methods in Generating Return**. This study examines the utilisation of natural language processing. To this end, it investigates whether a sentiment analysis of employee reviews provides any additional piece of information compared with a simpler proxy, start ratings, for generating returns.

4. **Exploratory Analysis of Ratings and Reviews**. Since analyses of reviews and

ratings from Glassdoor and similar platforms are quite scarce, mainly because of unavailability of any public API, an exploratory analysis of the scraped data is conducted as a part of this thesis and is presented throughout the text and in the Appendix.

The following sentiment scoring methods are considered:

1. Score reviews consisting of concatenated pros and cons and then compute the arithmetic mean.
2. Follow the approach stated above and replace the averaging method with the weighted arithmetic mean based on the length of the reviews.

The key finding of this thesis is:

- A long portfolio using monthly differences in a three-month average sentiment based on ratings generates higher returns than the low risk-based counterpart. The average monthly return goes up from 0.30 % to 0.72 % (3.70 % and 9.00 % annually). Moreover, it exhibits a noticeably lower standard deviation of monthly returns than a momentum-based portfolio (1.20 % vs. 4.09 %).

Daniel Stancl, Employee Sentiment for Factor Investing in the Corporate Bond Market
Supervisors: Prof. Philip Treleaven, Daniel Beresford and Lucette Yvernault

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List of Acronyms

ANN	Artificial neural network
BERT	Bi-diractional Encoder Representations from Transformers
BoW	Bag of words
CNN	Convolutional neural network
CV	Computer vision
ESG	Environmental, social and corporate governance
FI	Fundamental investing
GRU	Gated recurrent unit
LSTM	Long short-term memory
ML	Machine Learning
NLP	Natural Language Processing
RNN	Recurrent neural network
SGD	Stochastic gradient descent

1. Introduction

The chapter introduces problems discussed in this thesis, outlines the motivation for this work, its research objectives, and empirical methods used to achieve them, concluding with an overview of the structure of the dissertation.

1.1 Motivation

Corporate bonds represent a convenient way of obtaining capital for stable companies all around the world. The US corporate bond market capitalisation is about 40 % of the global market, the largest of any country (Sifma, 2020). After the borrowing pile-up in 2019, the outstanding debt of U.S. non-financial companies rose to the unprecedented $13.5 trillion at the end of that year (Çelik et al., 2020). Although the EU and UK markets are considerably smaller, they still constitute an interesting investment opportunity. Research purely devoted to the drivers of corporate bond returns started appearing decades after the introduction of equity literature. Still, disputes persist over definitions of factors used for portfolio construction.

Factor investing relies on the idea of the possibility to generate portfolio returns beyond the market premium by harvesting excessive risk premium, which is associated with selected characteristics. Furthermore, a side effect of this investment approach is an enhancement of portfolio diversification as these drivers do not have to be necessarily highly correlated with macroeconomic variables, and thus exhibit low beta with a market.

This thesis extends the recent research of factor models for corporate bond portfolios, for example, by Houweling and Van Zundert (2017). That and other studies successfully adopted a range of well-documented factors in equity literature, but definitions of factors vary across individual papers. These factors, initially explored for stock returns are low risk, value, size, momentum and carry. These characteristics are, therefore, covered in this work, though they are not all examined due to the limited availability of corporate bond data.

In recent years, the escalation of responsibility for sustainability issues among investors has been observed. This resulted in integrating alternative non-financial data into their investment decision process. These unconventional risk assessment criteria are environmental, social and governance (ESG) factors. Even though the first studies emerged already in the 1970s, adoption of these gauges has been sluggish, mainly because of concerns over their potentially negative impact on portfolio returns.

However, the ubiquity of alternative data, including textual or satellite and many other, and the possibility of investigating them gradually accelerated consideration of such information during portfolio constructions. This was enabled by a rise in computational resources together with invention of new powerful machine learning (ML) algorithms. Among others, sentiment analysis, a subfield of natural language processing (NLP), whose aim is to analyse people's sentiment, emotions or opinions expressed in the text, has attracted considerable attention of academic and commercial researchers (Liu, 2012).

Glassdoor, one of the world's largest job sites, where employees share information about their current and former employers, contains amounts of data potentially exploitable as one of the predictors of performance of companies' securities. The relationship between employee satisfaction and future stock returns has already been investigated and started with a study by Green et al. (2019), which used reviews from Glassdoor as well. This dissertation aims to utilise a similar technique in the corporate bond market.

1.2 Research Objectives

The main objective of this thesis is to investigate whether employee sentiment about companies has any statistically significant predictive power for the returns on corporate bonds. To achieve this, a series of experiments, described in Section **1.3** has been conducted to pick the bonds for the long-short and long portfolios.

Subsequently in the simplified manner, the portfolio returns are calculated and investigated based on whether the employee sentiment has a predictive usefulness to estimate future bond prices trends. The results are also compared with momentum-based and low-risk portfolio returns.

1.3 Research experiments

The following research experiments are conducted in this thesis:

1. **Investigation of Employee Sentiment based on Ratings in Generating Return**. This experiment investigates the use of analysis of employee ratings for a factor model and its power in generating return using own constructed factor long-short and long-only portfolios. On this occasion, the company's sentiment score is derived as an arithmetic mean of its ratings.

2. **Comparison of Different Sentiment Scoring Methods in Generating Return**. This study examines the utilisation of natural language processing (NLP). It, therefore, investigates whether a sentiment analysis of employee reviews provides any additional information compared with a simpler proxy, star ratings, for generating returns. In order to calculate sentiment for each company, the following approaches are considered:

   - Score reviews consisting of concatenated pros and cons and then compute their arithmetic mean.

   - Follow the approach stated above and replace the averaging method with weighted arithmetic mean based on the length of the reviews.

   In all cases, pre-trained language model - Bidirectional Encoder Representations from Transformers (BERT) - is used for estimating sentiment score.

1.4 Scientific Contributions

This thesis contributes to the existing literature in the following ways:

1. **Factor model Incorporating Employee Sentiment for the Corporate Bond Market**. This thesis builds the model fed by monthly bond data and company's sentiment calculated from Glassdoor reviews and ratings. This model in an automatic way picks the bonds for a portfolio. Subsequently, the framework calculates estimated returns.

2. **Data Retrieval and Database Pipeline**. This work engineers a pipeline for scraping employee reviews and related information from Glassdoor. This is attained using a Python's Selenium-based crawler and subsequently storing them in the database built using Django making the data easily available for possible future endeavours of other students and researchers.

3. **Exploratory Analysis of Ratings and Reviews**. Since analyses of reviews and ratings from Glassdoor and similar platforms are quite scarce, mainly because of unavailability of any public API, an exploratory analysis of the scraped data is conducted as a part of this thesis and is presented throughout the text and at the Appendix.

1.5 Thesis Structure

The rest of this thesis is organised as follows.

Chapter 2 provides an overview of related research fields, starting with factor investing in the corporate bond market, followed by an ESG approach to the risk assessment and sentiment analysis and its utilisation in ESG investing. **Chapter 3** outlines company selection criteria together with sources, characteristics and pre-processing of the data used for this study.

Chapter 4 then introduces tools developed for data retrieval and storage. It continues with approaches used for employee sentiment scoring and corresponding proposed modifications to the factor model. **Chapter 5** evaluates the ability of employee sentiment in generating returns. This is subsequently discussed in **Chapter 6** and it is followed by a future research proposal. Finally, **Chapter 7** reviews key findings and scientific contributions of this work and concludes this report by presenting the most promising direction for research.

2. Background and Literature Review

This chapter provides background information on key research concepts this thesis focuses on such as factor investing in the corporate bond market and an ESG approach to risk management. This is followed by a survey on sentiment analysis and the used language model - BERT. The final section reviews existing literature on sentiment analysis in ESG investing.

2.1 Factor Investing in the Corporate Bond Market

”Factor investing is the investment process that aims to harvest the risk premia through exposure to factors.” ”A factor can be thought of as any characteristic relating a group of securities that is important in explaining their return and risk” (Bender et al., 2013). A formal notion about factor investing was initially made in Ross (1976), where the author followed on his previous co-authored study Ross et al. (1973). There, Ross stated the future returns were correlated with various financial factors, i.e. there existed a linear relationship between them. In those times, this investment framework was proposed as an alternative to two paramount theoretical approaches - modern portfolio theory[1] (MPT) (Markowitz, 1952) and state preference theory[2] (SPT) (Hirshleifer, 1966). Importantly, the relaxation of various rigid assumptions, including normal distribution or quadratic preference for MPT and SPT respectively, was suggested as appealing characteristics of factor investing (Ross, 1976).

Nowadays, corporate bond literature on factor investing predominantly springs from the equity's counterparts. Even some contemporary studies attempted to directly apply characteristics explaining stock excessive returns into the universe of companies' debt investing (Chordia et al., 2017). However, this attitude is put in doubt by the more recent research like Israel et al. (2017), where authors pointed out that pertinent risks across credit and equity markets

[1] MPT strives for return maximisation with respect to a given amount of quantifiable risk. The risk of portfolio is intended to be regulated by diversification.

[2] SPT approaches uncertainty in a way that ”commodities can be differentiated not only by their physical properties and location in space and time but also by their location in 'state'. By this, it for instance, means that 'ice cream when it is raining' is a different commodity than 'ice cream when it is sunny'” (Tirimba, 2014).

differ. They further warned that, even though corporate bond and equity prices were not independent, they did not react equally to changes in the company's assets. Moreover, there were distinct factors for both equities and bonds, which affected their prices, and also corporate bond and equity markets were not identical. It is, therefore, appropriate credit investing to be considered from its own perspective.

Endeavours have been thus dedicated to finding variables having alpha specifically in the corporate bond market. These characteristics, although inspired by the world of equities, now have their own definitions for corporate bonds, but some disputes around have been lingering. While papers devoted to multi-factor credit portfolios are still scarce, there is, nowadays, evidence for **low risk**, **value**, **size**, **momentum**, **carry** and **quality**, which are also covered in this chapter.

These characteristics are usually used to construct a long-only or long-short portfolio in a way that a certain percentage of best-performing bonds, according to a given factor, are bought, and the worst-performing are sold. Subsequently, alpha of the portfolio can be estimated using Capital asset pricing model (CAPM) as

$$R_t = \alpha + \beta_t \cdot R_M + \varepsilon_t, \tag{2.1}$$

where R_t is a return on the portfolio, and R_M denotes a market rate of return. According to Chen et al. (2014b), it is appropriate to distinguish between investment-grade and high-yield bonds, as these represent two distinct spheres of credit universe. For this reason, depending on the bond class, investment-grade and high-yield index, respectively, are usually used as R_M in model (**2.1**) to evaluate excess returns.

There are also more advanced regression models to describe portfolio returns at time $t + 1$ predicted from factors at time t, which achieve higher R-squared, namely:

- Fama-French three-factor model (Fama and French, 1993),
- Fama-French-Carhart four-factor model (Carhart, 1997),

nevertheless, for the sake of the scope of this thesis, these frameworks are not elaborated here.

2.1.1 Definition of Selected Factors

Low risk

Long-position investing in low-risk assets has been documented since the work of Haugen and Heins (1972), where the hypothesis that higher risk generated excessive returns was rejected. There, researchers' experiments, moreover, suggested that low-risk portfolio provided higher average reward in the long run. Many years later, Frazzini and Pedersen (2014) supported the proposition that investing in low-beta[3] assets yielded higher return, and provided evidence on a broad range of financial instruments including equity, futures, government and corporate bonds. In that study, ratings and maturity were used as a measure of risk for corporate and Treasury bonds respectively.

Here, the methods are inspired by a definition of Ilmanen (2011), and then followed by Houweling and Van Zundert (2017), suggesting to buy bonds with higher ratings and shorter maturity and sell worse rated, long-dated ones. I restricted on the maturity only.

Value

Value investing in equity markets has been also well documented for decades with the first occurrence already in the 1970s (Basu, 1977). In this experiment, Basu proposed cheap stocks tended to outperform their more expensive counterparts in terms of risk-adjusted return. In order to determine how expensive a given share is, prices of a security are commonly compared with a company's fundamental value, for example earning, thus low P/E ratio[4] suggests to buy a stock.

Correia et al. (2012) were among the first researchers who investigated the applicability of the concept of value in the corporate bond market. They tested different accounting-based and market-based (both equity and credit) information for explaining ex-post credit returns and found strong evidence that the difference in implied and actual credit spreads[5] had robust predictive power in explaining future bond returns. Houweling and Van Zundert (2017) further restricted themselves only to credit-related risk measures and derived "true" credit spread from a cross-sectional regression as

$$S_i = \alpha + \sum_{r=1}^{R} \beta_r I_{ir} + \gamma M_i + \delta \Delta S_i + \varepsilon_i, \tag{2.2}$$

where S_i denotes a credit spread of bond i, I_{ir} stands for a dummy variable denoting a rating class of bond i, i.e. $I_{ir} = 1$ when bond i belongs to class r and 0 otherwise. M_i is maturity of bond i, and ΔS_i captures the three-month change in the credit spread of bond i.

Accordingly, bonds exhibiting a higher difference between actual and implied credit spreads should be longed, while the ones with low disparity are to be shorted.

Size

Also, the relationship between the total market capitalisation of stocks traded at exchanges and future returns has been examined for decades beginning with a seminal work of Banz

[3] Beta measures a volatility of a security in relation to the market

[4] P/E ratio = (stock price) / (earnings)

[5] Credit spread denotes a difference in yield between two bonds of similar maturity. The common practice is to use Treasuries or other government bonds as a base for the calculation.

(1981), where Banz on the sample of common stocks traded at NYSE provided evidence that smaller companies generated a higher risk-adjusted return in average.

For a long time, there was no study, which would have shown how alpha in the corporate bond market was associated with a size factor. The first attempt was made by Houweling and Van Zundert (2017), who demonstrated there was a statistically significant positive relation between a corporate bond's excessive return and total company's public debt. Importantly, the results held both for multi-factor long-only and single factor long-short portfolios. Similarly, the usefulness of a size factor was experimentally supported by Henke et al. (2020), for single- and multi-factor long strategies.

Momentum

Jegadeesh and Titman (1993) documented that long-buying or short-selling (and holding the position for six months) stocks that performed best or worst, respectively, in the preceding 6 months, is a strategy that tends to significantly outperform the market. The researchers also found a large portion of winners' and losers' momentum had been likely to vanish for long-term portfolios within two years since the formation.

Jostova et al. (2013) showed, on the large sample of U.S. corporate bonds between the years 1991 and 2011, strong momentum profitability in this market for the 3-, 6-, 9- and 12-month formation and holding periods. Moreover, their study proposed momentum was predominantly driven by high-yield bonds, which explained the shortage of momentum before 1991. The presence of momentum in the European corporate bond markets was analysed and confirmed by Barth et al. (2017), and the authors as well claimed it mainly arose among the non-investment bonds. Validity of momentum credit portfolios was further endorsed by multi-factor corporate bond literature [(Houweling and Van Zundert, 2017), (Israel et al., 2017)]. The last two studies relied on six months of trailing credit returns. Israel et al. (2017), furthermore, considered a half-year equity momentum.

Carry

For a long time, carry was predominantly studied for currency markets. Recently, endeavours to apply this characteristic to other asset classes have emerged. Koijen et al. (2018) were amongst the firsts who tried to propose a general definition of a security's carry. According to them, an asset's return can be decomposed into several parts

$$R_t = \text{carry}_t + \underbrace{\mathbb{E}(\text{price appreciation})_t}_{\text{expected return}_t} + \text{unexpected return shock}_t \tag{2.3}$$

In this setting, "that carry is a model-free characteristic directly observable ex-ante from futures (or synthetic futures) prices" (Koijen et al., 2018).

Specifically for finite-maturity securities such as bonds, the carry, at time t with a maturity of τ time periods, from equation (**2.3**) can be calculated as

$$\text{carry}_t^\tau = \frac{S_t^{\tau-1} - F_t^\tau}{F_t^\tau}. \tag{2.4}$$

In equation (**2.4**), F_t^τ denotes the futures price at time t, and τ is a time to maturity, expressed in time periods, of an underlying security.

Quality

In general, quality investing is based on a set of fundamental qualitative and quantitative measures used for identifying companies with desired characteristics. This kind of investing is quintessential for fundamental investors, which is a hugely broad field and thus beyond the scope of this thesis. Therefore, the related information can be sourced from the corresponding literature such as (Graham and McGowan, 2005).

In an academic sphere, for example, Novy-Marx (2014) stemmed from Graham's studies and used his five quality criteria:

1. short-term company's financial health indicated by a current ratio[6]
2. strong financial position determined by a net current assets to long term debt ratio,
3. company's earnings stability measured by past positive earnings in 10 preceding years,
4. uninterrupted dividend payments in last 20 years,
5. growing earning-per-share

The author added one point to each company if a given criterion was achieved by that enterprise in order to quantify these characteristics. This score then represented a signal employed during the company selection process.

2.1.2 Multi-Factor Models

Portfolio construction using a multi-factor model is very similar to a single-factor model. Only instead of choosing securities according to one characteristic, various single-factor different portfolios of an equal allocation are built. These then comprise one multi-factor portfolio (Houweling and Van Zundert, 2017). This approach should benefit from low correlation between individual determinants and thus provides higher returns.

In the last 5 years, more attention has been paid to the investigation of the validity of multi-factor models in the corporate bond markets. Israel et al. (2017) demonstrated the ability

[6] Current ratio measures the ability of the company to meet its short-term liabilities. Current ratio is usually calculated as current assets over current liabilities.

of a combination of four characteristics - carry, low risk, value and momentum - to generate positive statistically significant risk-adjusted profit. Furthermore, their results held both for long-and-short and long-only portfolio strategies.

Houweling and Van Zundert (2017) conducted separate comprehensive analyses for investment-grade and high-yield corporate bonds. They gave evidence that a combination of four factors - low risk, value, size and momentum - appropriately balanced between more prudent and risky characteristics, measured by Sharpe ratio, for both credit classes. Moreover, their investment strategy based upon their multi-factor model always generated higher alpha, in CAPM and Fama-French-Carhart model frameworks, than low-risk and momentum portfolios. This excessive return was, furthermore, statistically significant at the 1% level in all cases. On the other hand, value and size portfolios, which yielded higher alpha, were statistically significant at the 1% level in 1 out of 2 cases for high-yield bonds and not even single once for investment-grade class.

Five characteristics - carry, quality, value, size and momentum - were used and combined by Henke et al. (2020). Their analysis, which was again conducted on U.S. investment-grade and high-yield bonds, manifested that the multi-factor model outperformed single-factor ones in terms of risk-adjusted returns. The authors of that study attributed these results to low correlation between individual factors.

2.2 ESG Investing and Its Adoption

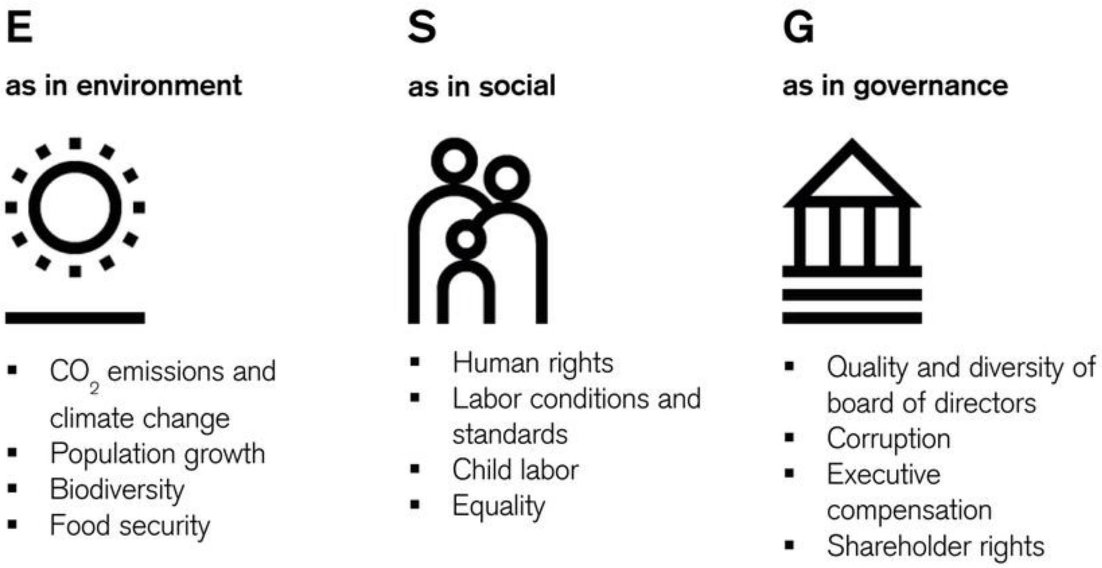

Figure 2.1: Meaning of ESG
Source: (ESG, 2018)

Two interwoven terms - ESG investing and socially responsible investing (SRI) - were referred by academics throughout time. An agreement on their definitions and appropriate names, nonetheless, was missing (Eccles and Viviers, 2011). One of the first mentions considering these two concepts together was made by Sparkes (2001), where the author was concerned with ethical and responsible investment. He postulated that SRI is an investment approach taking ESG and related criteria into account with an aim to maximise risk-adjusted returns. The phrases ESG and related criteria are used deliberately, as researchers in the more recent literature were inclined to the stance that terms ESG and alternative data were interchangeable (In et al., 2019). The authors of the last study pointed various sources of such data out, including, for instance, satellites or smartphones. They also emphasised the broadness of ESG data.

However, concerns over the potential negative impact of the socially responsible investment process on the funds' returns, along with low expressed ethical responsibility in the past century may have dragged an adoption of these non-financial assessment instruments. Notwithstanding early evidence that non-financial characteristics did not necessarily sacrifice portfolio returns [(Mallin et al., 1995) for the U.K., (Guerard, 1997) for the U.S.], the scepticism persisted (Sparkes, 2001). Therefore, a lot of empirical research has been devoted to this issue since then.

Friede et al. (2015) conducted an extensive analysis of more than 2000 empirical studies published since the 1970s, where the authors investigated the relation between ESG criteria and the financial performance of companies. Their work provided evidence for a positive correlation between these two measures with findings there were many opportunities on multiple equity and non-equity markets for market-outperforming ESG investments. However, the authors also stressed the fact that the investors' perception to this asset management approach were still pessimistic mainly because investors were worried about negative effects of accounting for non-financial criteria on portfolio returns. The reluctance of investors and fund managers to rely on alternative data was ascribed to the lack of understanding of the incorporation of this information into the investment decision process.

Adoption of ESG factors by asset managers in the U.S. and Europe was probed by Van Duuren et al. (2016), where the authors focused on individual ESG dimensions and evaluated to which degree this information was used by investors. They identified the perception of integration differs between the U.S. and Europe, with European managers being more favourable to this approach. This dissimilarity was attributed to the perspective on SRI across continents, as European peers deemed this to be closer to fundamental investing (FI). The authors further found governance dimension to be the predominant centre of interest, which was considered to be closely related to long-run corporate financial performance and thus this companies' assessment aligns with the concept of FI. The researchers, moreover, concluded the conscientious investors preferred company-level analyses to the industry-level ones, which was interestingly similar to the asset managers' attitude in the 1980s as earlier explored by Chugh and Meador

(1984).

2.3 Sentiment Analysis and Related Machine Learning Theory

2.3.1 Sentiment Analysis and Machine Learning Basics

Sentiment analysis is a subfield of statistical NLP whose roots stretch to 1950. For example, Harris (1951) tried to find automatic methods for analysing various language structures. However, this empiricist approach was subsequently replaced by methods of rationalists for a couple of decades (Manning and Schutze, 1999). The resurgence of the statistical-based branch has been then observed since 2000 with a growth of industry applications, publicly available textual data sets and a rise of computational resources (Liu, 2012).

A current definition of this practice can be that: ”sentiment analysis, also called opinion mining, is the field of study that analyzes people’s opinions, sentiments, evaluations, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes” (Liu, 2012).

Liu (2012), furthermore, distinguished analysis of sentiment on three different levels:

- **Sentence** - The aim is to decide between positive, negative and neutral subjectivity of a single sentence.
- **Document** - This task broadens the scope of the previous one and focuses on determining sentiment of whole documents, which was considered, for example, by Pang et al. (2002).
- **Entity and Aspect** - This approach tries to reveal not only the sentiment of a sentence or document, but also find out what specifically people like and dislike in a given text (Hu and Liu, 2004).

There are two main approaches (which can be combined) to determine the sentiment of a text: a rule-based approach and a machine-learning-based approach.

Rule-based sentiment analysis uses a dictionary that determines whether the valence of a word or phrase is positive, neutral, or negative. The score for a sentence or document is then obtained by simply counting all positive and negative instances. Alternatively, the dictionary may assign to each word or phrase a number that quantifies its valence, and then the sum of such numbers (or two sums - one for positive, one for negative numbers) yields the overall sentiment score of a text.

The machine-learning-based approach to sentiment analysis, which is used in this dissertation, is more powerful. It consists of pre-processing of textual data in the first step. The text transformation, feature engineering and their role in sentiment analysis are well described by Haddi et al. (2013). But in short, this process usually involves:

- removing all special characters, numbers, URL links, etc.,
- erasing stop words - this term refers to common words in text, for example: *a, the, be, on, of*,
- expanding contractions,
- stemming or lemmatisation,

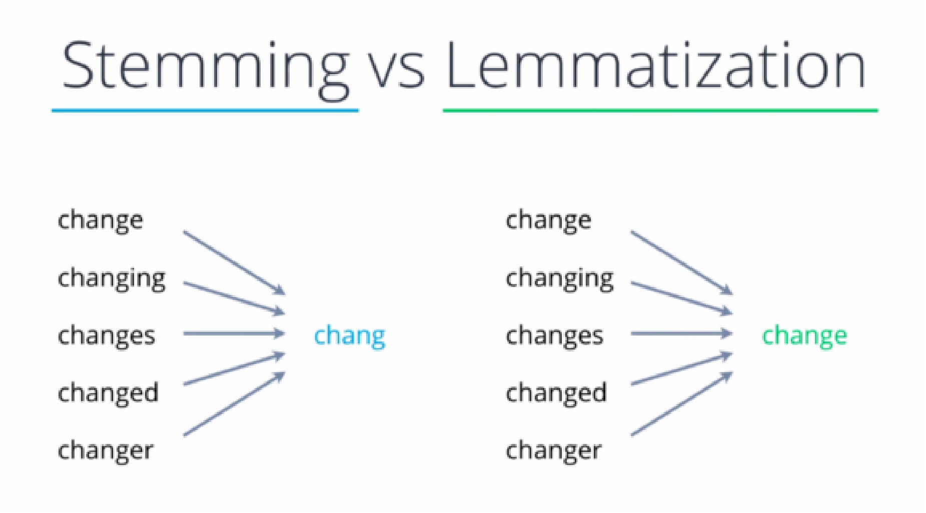

Figure 2.2: Stemming vs Lemmatisation
Source:

- removing white spaces introduced during the preceding steps,
- tokenisation.

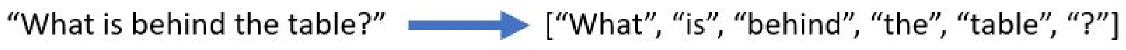
“What is behind the table?”
[“What”, “is”, “behind”, “the”, “table”, “?”]

Figure 2.3: Tokenisation

These pre-processed data are then used to create a document-term matrix. The document-term matrix is a mathematical matrix carrying the frequency or indication of words or n-grams[7] which occurre in individual sentences or documents. Here, each row corresponds to the analysed passage of text, and each column belongs to a unique word or n-gram. This matrix is then used as an input into a conventional machine learning (ML) algorithms such as logistic regression, random forest, support vector machine and others. These models can be called bag-of-words (BoW) models.

[7] An n-gram is a contiguous sequence of words.

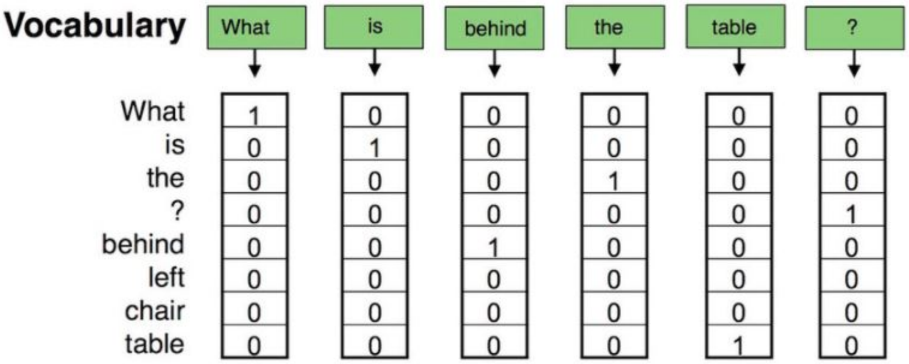

Figure 2.4: Bag of Words
Source: (Malinowski and Fritz, 2016)

In order one of these models to be able to learn polarity of words via model weights, it must be further provided with targets, and a loss function that should be minimised. In classification, the target is a label of an observation's output class and is represented as a one-hot vector for the ML model. In case of sentiment analysis, the target captures whether an input text is positive, negative or neutral. The loss function is simply a differentiable criterion measuring how well the algorithm fits the data and it is aimed to be minimised. For classification tasks, the cross-entropy loss, which is formulated as

$$\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}; \mathcal{D}) = -\frac{1}{N} \sum_{i=1}^{N} \sum_{k=1}^{C} y_k^{(i)} \log \hat{y}_k^{(i)} \tag{2.5}$$

is commonly used. In equation (**2.5**), $\hat{\mathbf{y}}$ represents a vector of probabilities the ML algorithm assigns to individual output classes, and $\mathbf{y}$ is the one-hot vector depicting an underlying truth. Index i refers to observation i out of N samples, and k indexes output classes.

$\mathcal{D}$ is an informal notation emphasising the loss is computed over the whole sample drawn from some distribution. The loss $\mathcal{L}$ is usually minimised with respect to a validation set rather than training data itself. Validation set can be considered as a random sample drawn from training data which is not seen by the ML model during an optimisation process. This ensures the algorithm tends to learn an underlying function behind $\mathcal{D}$ rather than just memorising labels for training data.

Mathematically, the task described above thus can be expressed as the following problem

$$\begin{aligned} \hat{\mathbf{y}} &= \operatorname{softmax}\left(f_A(\mathbf{x})\right), \ \mathbf{x} \in \{0,1\}^n \\ s.t. \ \min \ & \mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}; \mathcal{D}), \end{aligned} \tag{2.6}$$

where $\mathbf{x}$ denotes a vector of ones and zeros capturing word or n-gram occurrence in an analysed text. $f_A(\cdot)$ denotes any predictive algorithm. Softmax is a function mapping output values of $f_A(\cdot)$ into the probability space

$$\text{softmax}(x_j) = \frac{e^{x_j}}{\sum_{i=1}^{K} e^{x_i}}. \tag{2.7}$$

Since commonly there is no analytical solution for problems like (**2.6**), numerical iterative methods are used. The most simple technique is a gradient descent, first mentioned a long time ago by Cauchy (1847). This algorithm minimises a differentiable function L until convergence as

$$\mathbf{w}_{n+1} := \mathbf{w}_n - \alpha \nabla L(\mathbf{w}_n),\ n = 0, .., N \tag{2.8}$$

where $\mathbf{w}_n$ represents model's weights, and n is a training step. ∇L denotes a gradient of the given function L, and α is a learning rate or also called step-size. In full gradient descent, the whole training set is used to evaluate $\nabla L(\mathbf{w}_n)$.

More recently, this approach has been supplanted by stochastic gradient descent (SGD) (Robbins and Monro, 1951). SGD uses only random samples of training examples to estimate gradient and thus tends to be much faster than full gradient descent. Furthermore, the noise introduced by random sampling helps the algorithm to avoid stopping in local, but non-global, minima (Bottou, 1991).[8]

2.3.2 Advances in NLP and Sentiment Analysis - Neural Networks

Word embeddings

A considerable disadvantage of BoW is its disregard for semantic similarity between words and phrases.[9] As research on artificial neural networks (ANNs) ramped up, the simple, but a bit toothless BoW was replaced by a continuous high-dimensional representation of words, so called word embedding (usually vectors of a dimension between 50 and 300 are used)[10]. There is no rule defining what dimensions should represent and they are thus fully learnt by a model. Figure **2.5** depicts an illustrative example of how words are represented in vector space.

The word embedding was initially introduced in Skip-Gram model (Mikolov et al., 2013a), and soon after in GloVe (Pennington et al., 2014a). Let w be a corpus of words and c be their contexts. Furthermore, suppose D denotes a set of all (word, context) pairs. The Skip-Gram model then tries to find values of parameters θ maximising the following probability

$$\arg\max_{\theta} \prod_{(w,c)\in D} p(c|w;\theta), \tag{2.9}$$

[8] In an ideal case, the loss function would be strictly convex so that it can be easily minimised. In practice, however, this function is much more erratic with several local minima.

[9] One-hot vector representation is incapable of capturing how close two words are in semantic meaning, therefore, this important information is inevitably lost.

[10] Novel architectures, such as BERT, relies, for example, on 768-dimensional embedding.

where $p(c|w;\theta)$ is a softmax function,

$$p(c|w;\theta) = \frac{e^{v_c \cdot v_w}}{\sum_{c' \in C} v_{c'} \cdot v_w}, \tag{2.10}$$

In equation (**2.10**), $v_c, v_w \in \mathbb{R}^d$ denote vector representations of context c and words w, respectively, and $d \in \mathbb{N}$ is a dimension of considered vector space (Goldberg and Levy, 2014). The model learns the vector representation in an unsupervised manner. A description of this whole procedure is beyond the scope of this dissertation, and an interested reader may be referred to the following papers to get fully familiar with this technique [(Mikolov et al., 2013a), (Mikolov et al., 2013b), (Goldberg and Levy, 2014)].

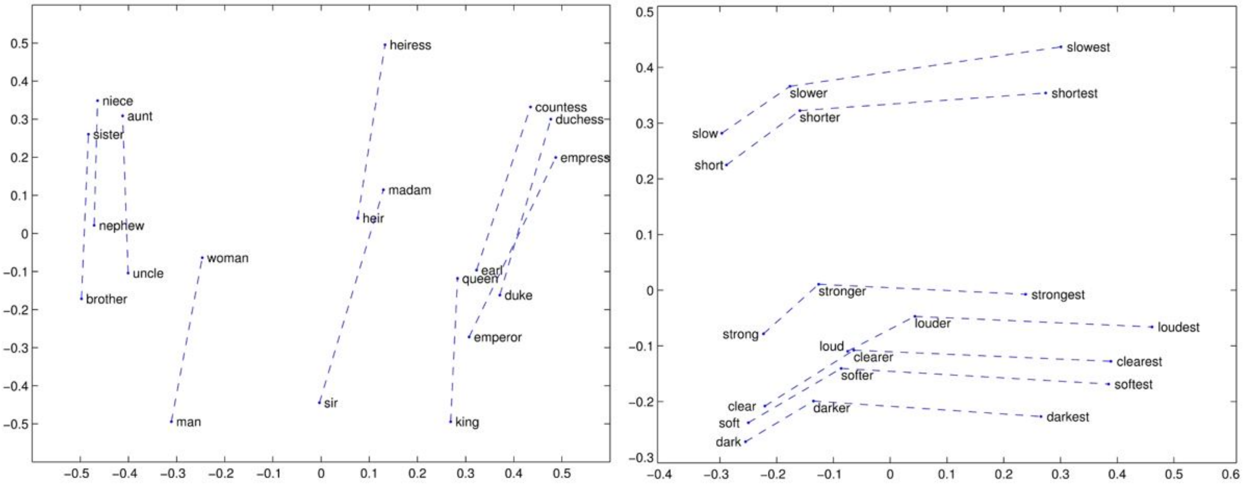

Figure 2.5: GloVe: Nuances between (i) man-woman, and (ii) adjective-comparative-superlativ
Source: (Pennington et al., 2014b) and (Pennington et al., 2014a)

GloVe partially stems from the methodology used in the Skip-Gram models, i.e. it leverages linear substructures capturing the similarity between words. But it, furthermore, takes word counts into consideration. Hence, let X_{wc} denote a frequency of occurrences of word w in context c. According to Pennington et al. (2014a), their model aims to minimise the following cost function

$$J = \sum_{(w,c) \in D} f(X_{wc}) \left(w^{\top} c - \log X_{wc} \right), \tag{2.11}$$

where $f(\cdot)$ is a weighting function,

$$f(x) = \begin{cases} (x/x_{\max})^{\alpha} & x < x_{\max}, \\ 1 & \text{otherwise}, \end{cases} \tag{2.12}$$

$\alpha > 0$ (Pennington et al., 2014a).

The word embeddings can be used in ML algorithms either as a layer with pre-trained weights, which can be fixed throughout the training of the model or updated via back-propagation in a common way, or one can replace this by a single feed-forward fully-connected layer.

For the models utilising embeddings instead of the BoW, input representation given by equation (**2.6**) is no more suitable. The problem is thus re-defined as

$$\begin{aligned} \hat{\mathbf{y}} &= \text{softmax}\left(f_A(\mathbf{X})\right), \ \mathbf{X} \in \{0,1\}^{n \times m} \\ s.t. \ \min \ &\mathcal{L}(\hat{\mathbf{y}}, \mathbf{y}; \mathcal{D}), \end{aligned} \tag{2.13}$$

where $\mathbf{X}$ represents concatenated one-hot vectors of size n to the matrix of size $n \times m$, where m denotes a sequence length. Since the length of sequences differs, they are padded[11] so that they can be processed by ML models.

Neural-network-based model architectures

Moreover, in order to achieve state-of-the-art results, 'classical' ML algorithms were replaced by neural-network-based counterparts with significantly more trainable parameters. In general, a simple feed-forward neural network. which is the most basic form of an ANN, with a single hidden layer can be expressed as a compound function

$$\hat{\mathbf{y}} = g(f(\mathbf{x})), \tag{2.14}$$

where $\mathbf{x} \in \mathbb{R}^n$ is an input vector, and $\hat{\mathbf{y}} \in \mathbb{R}^k$ denotes a vector of output quantities. Functions f and g are affine transformations, potentially followed by an activation function. An affine transformation denotes the following projection:

$$f(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{b}, \tag{2.15}$$

where $\mathbf{x} \in \mathbb{R}^n, \mathbf{b} \in \mathbb{R}^m, \mathbf{A} \in \mathbb{R}^{m \times n}$. The illustration of an ANN with a single hidden layer is depicted in Figure **2.6**

The following variants of ANNs (or possibly their combinations) belong to the most popular choices in NLP:

- **Convolutional neural networks (CNNs)** - This type of network utilises convolutional layers, which use kernel filters with shared weights across the whole input object that are applied to neighbourhood features (LeCun et al., 1998). Although they were initially designed for image classification, Kim (2014) amongst others successfully tailored this technique to various sentence classification problems, including sentiment analysis, and got state-of-the-art performance on multiple tasks.

  An undoubted advantage of CNNs for text classification in comparison with recurrent

[11] Padding is a process of adding special tokens to each sentence in order all sentences in the data have the same length.

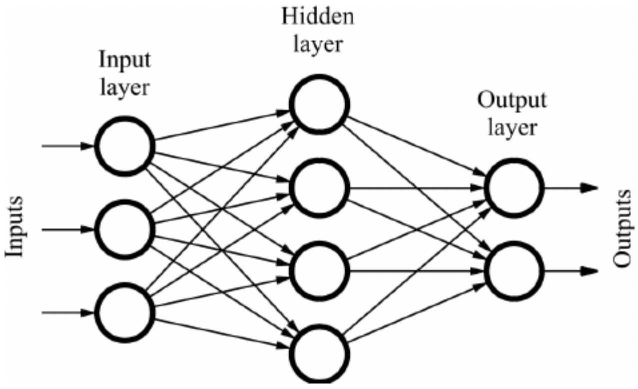

Figure 2.6: Feed-forward neural network
Source: (Quiza and Davim, 2011)

neural networks or versatile language models such as BERT is fewer trainable parameters, which results in less cumbersome and significantly shorter training. They, moreover, usually require only little hyperparameter tuning (Kim, 2014).

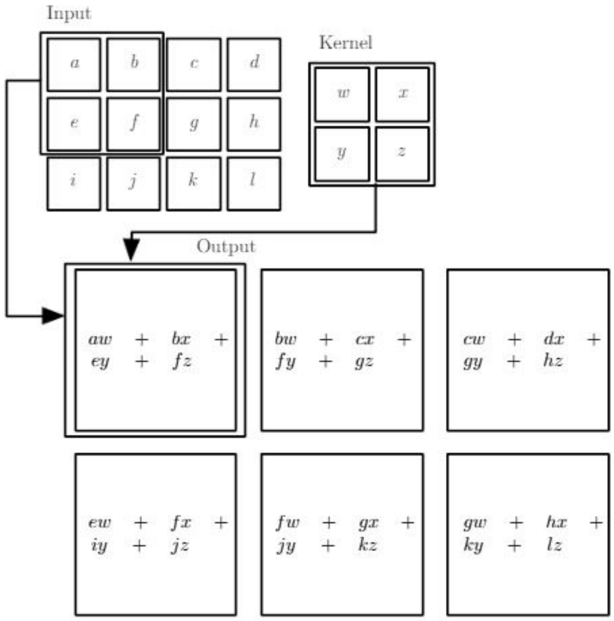

Figure 2.7: 2D Convolutional layer
Source: (Goodfellow et al., 2016)

- **Recurrent neural networks (RNNs)** - This class of ANNs, which was initially derived from feed-forward ANNs, uses an updated hidden (internal) state, which enables a model to store past information, and thus are perfectly fit for dealing with time-series or sequence data.

  RNNs were firstly introduced in the seminal paper of Rumelhart et al. (1986), however, their architecture was strongly modified because vanilla RNNs suffer from vanishing or exploding gradient which completely cramps their fitting process. This stems from training these networks via backpropagation through time, which is a consequence of recursively updated hidden state, i.e.

$$\mathbf{h}^{(t+1)} = \mathbf{W}^{\top}\mathbf{h}^{(t)}, \tag{2.16}$$

Eventually, this can halt training far from the optimum or can cause a model's weights will diverge. (Goodfellow et al., 2016).

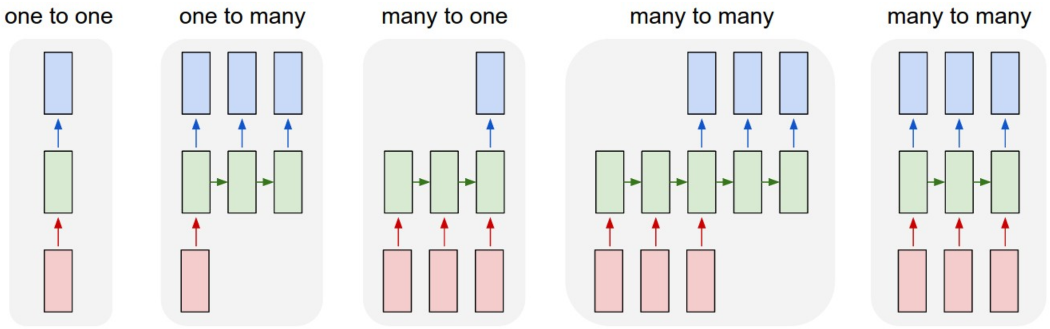

Figure 2.8: RNNs have internal state
Source: Karpathy (2015)

Motivated by these problems, Hochreiter and Schmidhuber (1997) and Cho et al. (2014) presented two mechanisms, long short-term memory (LSTM) and gated recurrent unit (GRU) respectively, employing a forget gate which controls an extent of past information to be kept. The whole mechanism is described with several equations, that can be found in two cited papers, but for simplicity one can consider this as a set of sigmoid functions determining which information should be kept and which forgotten and updated. The LSTM and GRU mechanisms helped to tackle the vanishing gradient but did not solve the exploding gradient, which was meanwhile simply resolved using clipping (Pascanu et al., 2013).

- **Transformer-based models**

2.4 BERT for Sentiment Analysis

This thesis uses the language model firstly presented by Devlin et al. (2018) called Bidirectional Encoder Representations from Transformers (BERT). BERT has been a new state-of-the-art language model that ”is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers” (Devlin et al., 2018). Consequently, the pre-trained model can be fine-tuned by adding a fully-connected layer on various tasks while achieving state-of-the-art results.

2.4.1 Architecture

BERT is based on the multi-layer bi-directional Transformer introduced in Vaswani et al. (2017). The key component of this model is the Transformer block consisting of two sub-layers, a multi-head self-attention, that is composed of a few parallel attention layers, and a position-wise fully-connected ANN. These two sub-layers are accompanied with residual connections (He et al., 2016) and a normalisation layer (Ba et al., 2016) to ease the optimisation process. Since a very good description of the transformer is provided in Vaswani et al. (2017), only the very crucial components are elaborated in this section.

Attention

The attention is the cornerstone of BERT. The attention mechanism was firstly used by Bahdanau et al. (2014) to enhance the performance of an encoder-decoder RNN model in neural machine translation tasks. The authors modelled the conditional probability of a next token, y_i, in the output sequence as

$$p(y_i|y_1, ...y_{i-1}, \text{input seq.}) = \text{Encoder-Decoder}(y_{i-1}, s_i, c_i), \tag{2.17}$$

where s_i is the model's hidden state used for emitting the output token, and c_i denotes a context vector, which contains information about the sequence that is concentrated around the position i.

In order to compute c_i, they made use of an additive attention defined as a weighted sum:

$$c_i = \sum_{j=1}^{T} \alpha_{ij} h_j, \tag{2.18}$$

where α_{ij} denotes a probability, which is an output of attention mechanism, and h_j represents annotation output by a decoder of the model. Attention, or also an *alignment model* according to Bahdanau et al. (2014) is then defined as

$$\alpha_{ij} = \text{softmax}\left(a(s_{i-1}, h_j)\right), \tag{2.19}$$

where a is a feed-forward network which is trained together with the whole model.

The alignment model can be understood as a network which tries to estimate the importance of h_j, considered with the previous hidden state s_{i-1}, for the next output token y_i. In other words, an attention mechanism decides which part of the input sequence the encoder-decoder should focus on (Bahdanau et al., 2014).

For BERT, the additive attention were replaced by scaled dot-product attention introduced by (Vaswani et al., 2017), who defined it as

$$\text{Attention}(\mathbf{Q}, \mathbf{K}, \mathbf{V}) = \text{softmax}\left(\frac{\mathbf{Q}\mathbf{K}^{\top}}{\sqrt{d_k}}\right)\mathbf{V}, \tag{2.20}$$

where $\mathbf{Q}, \mathbf{K}, \mathbf{V}$[12] represent queries, keys and values packed in matrices which determines a task attention functions are asked for (Vaswani et al., 2017). A scaling factor $\frac{1}{\sqrt{d_k}}$ is used to avoid vanishing gradient for too large output values. While both types of attention mechanism are conceptually similar, the latter one is much more efficient in terms of computation and memory.

Whereas an attention mechanism is quite powerful itself, it was shown the performance can be further boosted by the utilisation of so called multi-head attention. This is attained by running several attentions in parallel, whose output values are concatenated and then again put through the function once again yielding the ultimate output of the attention mechanism. This technique enables the model to jointly inference information from different positions in the input sequence (Vaswani et al., 2017).

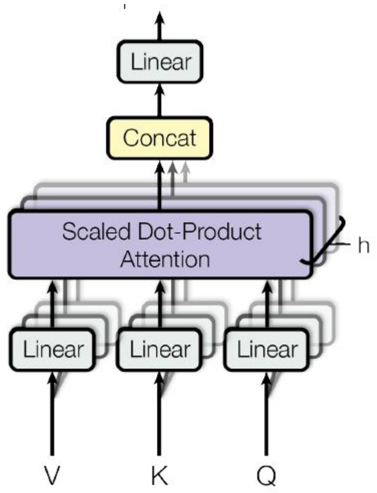

Figure 2.9: Multi-head attention
Source: Devlin et al. (2018)

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2.4.2 Pre-Training and Fine-Tuning

The power of BERT lies in the fact that the model is pre-trained in an unsupervised way, and then can be simply fine-tuned on various down-stream tasks regardless of whether it is a single-sequence problem like sentiment analysis, or a pair-sequence one such as question answering or machine translation. This versatility is possible by a tailored input/output representation described in Devlin et al. (2018). This is based on special tokens, and input

[12] $\mathbf{Q}, \mathbf{K}, \mathbf{V}$ are learnt matrices

and position embeddings helping the model to differentiate between single- and pair-sequence tasks, and between sequences A and B for the latter problem.

BERT is pre-trained on large corpora like English Wikipedia, which contains a couple of thousands million words, with 2 tasks (Devlin et al., 2018):

1. **Masked LM** - For the sake of simplicity, this is done via masking a certain percentage of tokens from input word embeddings, and these masked elements are then predicted by the model. The model is optimised with a minimisation of cross-entropy loss.
2. **Next sequence prediction** - This tasks helps significantly improves the performance of BERT on two-sequence problems by understanding the relationship between a couple of sequences. In this case, training data are represented by pairs of sequences and the model should predict whether the second sequence follows the first one, or it is just a random one. The objective is to minimise binary cross-entropy loss.

After this stage, fine-tuning follows. Fine-tuning of language models has been inspired by an accomplishment of a transfer learning in computer vision (CV), where researchers were attempting to deal with over-fitting of large-scale networks when trained on insufficiently large data sets. For example, Donahue et al. (2014) achieved state-of-the-art results on multiple CV tasks by transferring models on a different-purpose task by fine-tuning the last layer. Long et al. (2015) adapted various the then superb pre-trained classification CNNs on semantic segmentation and again got the very best results with a solid margin. In the latter case, the authors left unfrozen a few last layers during the training. Both approaches correspond with a suggestion not to transfer all model's layers at once as it may lead to forgetting already well learnt weights (Yosinski et al., 2014).

Later in NLP, fine-tuning had proved to be proficient between related tasks - sentiment analysis (Severyn and Moschitti, 2015), machine learning translation (Sennrich et al., 2015) or question answering tasks (Min et al., 2017). However, attempts to transfer models between dissimilar problems had been failing (Mou et al., 2016) until the endeavours of Howard and Ruder (2018) or Devlin et al. (2018)

In case of BERT, fine-tuning is pretty straightforward. Due to attention mechanisms and the specific model architecture, BERT is capable of handling various down-stream tasks by adding:

- a task-specific output layer that is appended at the top of the pre-trained model,
- special tokens (described in Devlin et al. (2018)) helping BERT to understand which problem should be learnt on.

Importantly, fine-tuning is significantly less expensive than pre-training itself, and therefore, in a few hours this model can be adapted to different NLP tasks on a single GPU (Devlin et al., 2018).

For the fine-tuning stage, this thesis does not use gradient descent presented in Section **2.3.1**, and it rather relies on a modern adaptive optimisation algorithm introduced in Kingma and Ba (2014) - Adam. Adam was proposed as a speed and memory efficient algorithm combining strengths of two other methods.

- AdaGrad (Duchi et al., 2011) - A variation of SGD with per-parameter adaptive learning rate substantially improving the robustness of an optimisation process.
- RMSProp (Tieleman and Hinton, 2012) - Another adaptive algorithm utilising moving averages of past gradients to evaluate the current step.

The Adam's single update step is more complex than gradient descent's one, however, it can be still summarised with a few formulas. Let m_0 (first moment estimate), v_0 (second moment estimate) and t (time step) be 0. Furthermore, set α=0.001 (learning rate), $\beta_1 = 0.9$ and $\beta_2 = 0.999$ (decay rates for moment estimates) and $\varepsilon = 10^{-8}$ (correction term), which are default parameters' values according to Kingma and Ba (2014). Suppose $\mathcal{L}$ be our loss function, and $\mathbf{w}$ denote model's parameters. Moreover, let g_t denote a gradient of loss function $\mathcal{L}$ with respect to model's weights $\mathbf{w}_t$, and g_t^2 represent an element-wise square, i.e. $g_t^2 = g_t \odot g_t$.

Then, the update step is illustrated in Algorithm **1**. Further details behind the choice of parameters can be found in the source paper (Kingma and Ba, 2014).

Algorithm 1: *Adam*: Update step
Source: Kingma and Ba (2014)

```
while $\mathbf{w}_t$ not converged do
    $t \leftarrow t + 1$
    $g_t \leftarrow \nabla\mathcal{L}(\mathbf{w}_{t-1})$
    $m_t \leftarrow \beta_1 \cdot m_{t-1} + (1 - \beta_1)g_t$ (update biased first moment estimate)
    $v_t \leftarrow \beta_2 \cdot v_{t-1} + (1 - \beta_2)g_t^2$ (update biased second moment estimate)
    $\hat{m}_t \leftarrow \frac{m_t}{1-\beta_1^t}$ (correct for bias)
    $\hat{v}_t \leftarrow \frac{v_t}{1-\beta_2^t}$ (correct for bias)
    $\mathbf{w}_t \leftarrow \mathbf{w}_{t-1} - \alpha \cdot \frac{\hat{m}_t}{\sqrt{\hat{v}_t + \varepsilon}}$
end
return $\mathbf{w}_t$
```

2.5 Sentiment Analysis in ESG Investing

Research on employee sentiment (regardless of whether we are talking about sentiment analysis in realm of NLP or not) and its relevance to the performance of securities followed on the findings on investors' and managements' sentiment and corresponding stock returns. For example, Chen et al. (2014a) found evidence between the stock returns and investors' opinion expressed via social media. In that study, the authors used articles and commentaries from Seeking Alpha. That and similar studies, however, cannot be assigned to the pure ESG literature.

Huang (2018) analysed more than 14.5 million product reviews posted by customers on Amazon.com. They constructed portfolio each month, longing on stocks of companies with abnormally high customer ratings and shorting for the ones with poor ratings within the past three months. An abnormal rating was defined as the difference between past-quarter mean rating and the average over the last year. Through the years from 2004 to 2015, the authors of this study were able to achieve average monthly alpha of 0.51 % 0.60 % (annualised rate of return: 6.29 % and 7.44 %) measured by Fama-French and Fama-French-Carhart models, and the excessive returns were highly statistically significant. These results were achieved on equal-weighted portfolio. The excessive returns with review-weighted portfolios even rose to the range of 0.77 % and 0.79 % (annualised rate of return: 9.64 % and 9.90 %). They, furthermore, showed that abnormal ratings were positively correlated with companies' returns and earnings surprises.

More recently, studies utilising crowd-sourced data sets of employee ratings and reviews have emerged. Green et al. (2019) used a data set of 1 million Glassdoor reviews for more than 1,200 unique companies. The researchers found a positive correlation between stock returns and improvement in the employee rating. At the end of each quarter in the period spanning over almost 9 years, they were constructing three different portfolios according to star rating change in the last quarter. These then consisted of companies from

- the top 20 %,
- the middle 60 %, and
- the bottom 20 %

the ranking of change in ratings. The equal-weighted portfolio of the top 20 % of companies yielded higher average monthly returns and alpha (according to the Fama-French-Carhart model) than the bottom counterparts by 0.84 % and 0.88 % respectively (annualised difference: 10.56 % and 11.09 %). These differences were claimed to be statistically significant at the 1% level. For value-weighted portfolio the differences was lower roughly by 0.1 % than in the unweighted case, but the results were again statistically significant at the 1% level.

Green et al. (2019), furthermore, noticed the effect was more detectable among current employees, novice ones and those ones writing longer reviews or working in the country of the headquarter. In other analyses, the authors found that ratings and reviews were related to the companies' cash flow and other financial fundamental information, which was likely to result in the predictability of stock performance.

The findings that an impact of employee sentiment and stock returns were more prevalent among certain groups of workers were also made by Chen et al. (2020). They used even a larger data set containing more than 1.7 million reviews of current employees for more than

3,600 enterprises. In that study, however, the researchers relied on a different methodology, and used employee sentiment index (ESI),

$$ESI = \frac{\#\text{positive reviews} - \#\text{negative reviews}}{\#\text{reviews}}, \tag{2.21}$$

instead of a change in the star rating. They concluded stocks associated with low ESI tended to outperform the higher-rated counterparts. In that case, the authors labelled all reviews with the star rating of 4 or higher as positive, and negative otherwise. This might be, however, a bit inconsistent with statistics of Green et al. (2019), who had found a mean and median star rating was 3.2 and 3.0 respectively, therefore the threshold of 4.0 may have lead to the biased data.

At the same time, quarterly (or possibly monthly) differences in star ratings seem to be a more valuable indicator than ratings themselves because star ratings are relatively well explained by various determinants, including company's size, return on assets, past stock returns and others, controlled for time and firms (Green et al., 2019). On the sample of roughly 16,000 quarter-firm-level observations for 1,200+ companies, the authors reported R-squared of 0.649 and 0.074 for star rating and changes in rating respectively regressed on the aforementioned variables.

The propitious results that employee expectations are associated with future stock returns were also confirmed by Sheng (2019). He further supported employees' feelings expressed online represent a huge amount of information, that can be harvested for the incorporation into the investment decision process, despite the fact that employees have no superior information about future returns of their firms [(Benartzi, 2001), (Cohen, 2009)].

Sheng (2019) on the sample of approximately 1 million Glassdoor reviews for more than 1,400 companies showed a positive correlation between abnormal positive outlook and future excessive returns. They, therefore, looked at the outlook, which is optional information filled in with reviews, and defined positive outlook as a fraction of reviews with a label of positive outlook. Abnormal outlook was then calculated as a different between positive outlook in the past month and the mean over three prior months. The companies were then sorted according to that factor and tercile portfolios[13] were created. It was found out that monthly excess returns of the top portfolios were higher by 0.86 % in average (annualised difference: 10.82 %) than the bottom ones, measured in the Fama-French-Carhart framework. Moreover this difference was statistically significant at the 1% level. The authors then constructed a long-short portfolio buying the top and selling the bottom tercile companies, which resulted in the ca. 0.7% monthly excess return (annualised excess return: ca. 8.73 %).

Even though there are multiple promising findings on the relevance of employee sentiment and returns in the stock market, to the best of my knowledge, there is no study investigating

[13] A term *tercile portfolios* denotes three portfolios of an equal size.

the relationship between this kind of sentiment and corporate bond returns. This aligns with the research focused on factor investing in the corporate bond market which is much less developed compared with an equity-oriented literature.

On the other hand, more recently, ESG-oriented analyses of sentiment in a combination with big data and ML appeared in other spheres. Serafeim (2020) used two data sets - ESG Performance scored by MSCI and more than 250,000 ESG-related articles for roughly 8,000 companies gathered by TruValue Labs used for the calculation of public ESG sentiment momentum - to show that long-short portfolios built upon the superior/inferior ESG performance and negative/positive sentiment momentum yielded significant alpha over the period of ten years.

3. Data - Selection, Sources and Exploration

This chapter outlines the selection criteria determining which companies are included in the study. Sources, characteristics together with some exploratory analysis, and pre-processing of market and employee sentiment data are also presented.

3.1 Company Selection Criteria

This thesis is based on information from three different sources:

- **Bloomberg** - market data on corporate bonds elaborated in Section **3.3**,
- **Glassdoor** - employee sentiment data described in Section **3.2**,
- **Yahoo Finance** - basic information about companies, including the sector and industry a given firm operates in, the country of headquarter, total revenue and a number of employees.

The data set used for this thesis is based on the sample of companies listed on three stock indices - S&P 500, FTSE 100, EURO STOXX 50 - and thus representing three different markets in the U.S., the U.K. and Europe.[1] This first choice criterion was determined by:

- companies included in stock market indices represent an easily available source of firms that can be scraped,
- the very limited amount of employee reviews and ratings for Asian markets. This is likely to be caused by a tendency of people to use different online platforms in these markets, as a similar effect can be observed with other online social media (Choi, 2020).

Due to the limited time assigned to the final project, this thesis works with the employee data in the relatively short period from July 1, 2018, to June 30, 2020, because of the lengthy scraping, which is justified in Section **4.1.1**. I, furthermore, narrowed the data set only to

[1] U.K and Europe companies are underrepresented compared with U.s. ones, however, it is not problematic as the firms are mainly studied within a single market.

the companies with at least 10 Glassdoor reviews over the monitored time frame of two years. This results in a sample of 605 companies spanning across 11 market sectors (Lake, 2020), and their distribution in individual markets is displayed in Table **3.1**.

	S&P 500	**FTSE 100**	**EURO 50**
Basic materials	18	9	4
Communication services	20	10	3
Consumer cyclical	63	15	6
Consumer defensive	36	11	5
Energy	23	2	2
Financial services	70	17	9
Healthcare	61	4	4
Industrials	69	10	7
Real estate	23	2	1
Technology	64	2	3
Utilities	25	4	3
Total	472	86	47

Table 3.1: Distribution of companies across stock market sectors

The sample of 605 firms is used for the exploratory analysis of ratings and reviews presented in this chapter and in the Appendix. However, since not all the companies issue bonds, I further retained only companies using public debt. Eventually, I ended up with the data set consisting of 350 business entities.[2]

	S&P 500
Basic materials	14
Communication services	15
Consumer cyclical	43
Consumer defensive	25
Energy	20
Financial services	58
Healthcare	45
Industrials	46
Real estate	15
Technology	46
Utilities	23
Total	350

Table 3.2: Distribution of companies issuing bonds across stock market sectors

Last, besides the selection criteria outlined above, I also coupled information on market data for Alphabet Inc. with the employee reviews for Google since there were significantly more

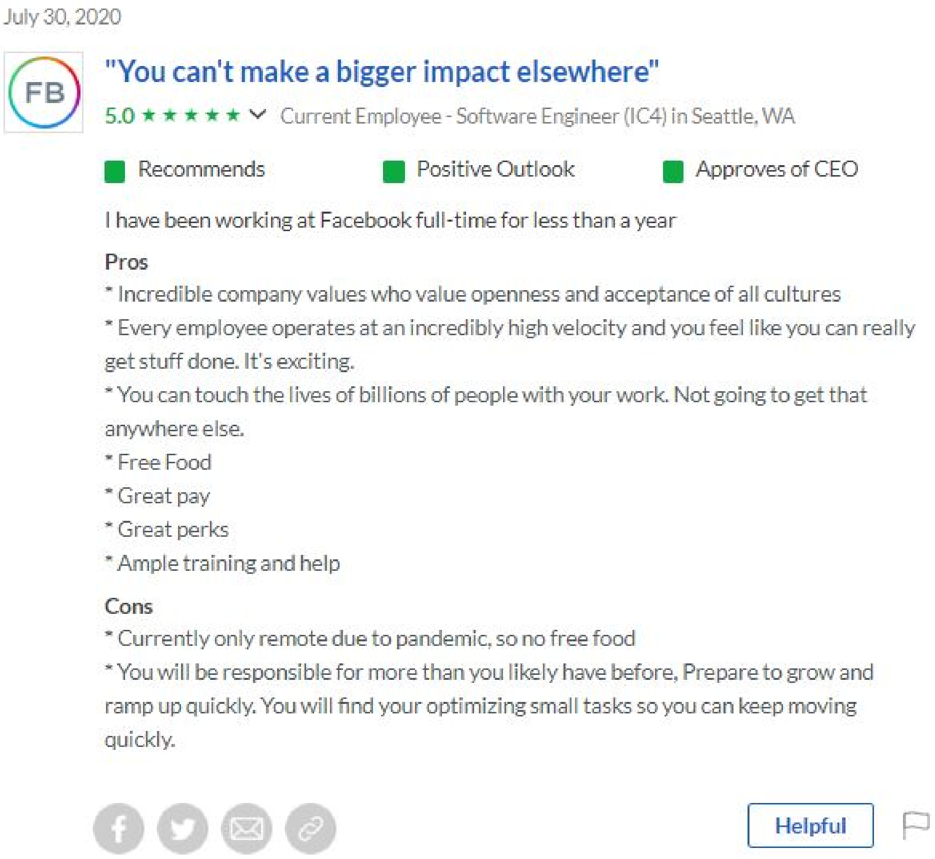
[2] I was able to collect corporate bond data using Bloomberg API only for three companies listed on FTSE 100 and EURO STOXX 50. As such, I decided not to include these data into the ultimate study.

Glassdoor records for the latter company, which is the major subsidiary of the aforementioned holding conglomerate.

3.2 Employee Sentiment Data

Glassdoor is one of the largest job sites in the world offering millions of job listings and represents a still expanding database of company reviews written by current or former employees (employee reviews and employee (star) ratings thereafter). There are also interview reviews and salary reports. As of July 2020, there were posted about 60 million reviews, salaries and insights on roughly 1 million employers. The websites were visited by approximately 50 million unique visitors each month (Glassdoor, 2020). I was given written express permission from a representative of Glassdoor to use all publicly available data via an e-mail.

All employee reviews are anonymous and consist of numerous elements describing the relationship between an employee and a company and his or her opinion on the firm.



July 30, 2020

"You can't make a bigger impact elsewhere"

5.0 ★★★★★ Current Employee - Software Engineer (IC4) in Seattle, WA

🟩 Recommends 🟩 Positive Outlook 🟩 Approves of CEO

I have been working at Facebook full-time for less than a year

Pros

* Incredible company values who value openness and acceptance of all cultures
* Every employee operates at an incredibly high velocity and you feel like you can really get stuff done. It's exciting.
* You can touch the lives of billions of people with your work. Not going to get that anywhere else.
* Free Food
* Great pay
* Great perks
* Ample training and help

Cons

* Currently only remote due to pandemic, so no free food
* You will be responsible for more than you likely have before, Prepare to grow and ramp up quickly. You will find your optimizing small tasks so you can keep moving quickly.

Figure 3.1: An example of employee review posted on Glassdoor
Source: Glassdoor

Individual components of the reviews are:

- Date - Date a review was posted.
- Main title - This is also used as a review link, and there is no specification on the content of this field.
- Star rating - The rating on scale 1 to 5 which consists of five sub-components: *Work/life balance, Culture & Values, Carrer Opportunities, Compensation and Benefits* and *Senior Management.* For this thesis, only the aggregated score is used, however, the scraping tool can be easily upgraded to download these sub-elements.
- Job title - An item specifying job title altogether with information on whether the review author is a current or former employee.
- Job location - Location of a unit an employee has been or was working at.
- Recommendation - Two pre-defined options: *Recommends, Does not recommend*
- Outlook - Three pre-defined choices: *Positive, Neutral, Negative*
- CEO - Three pre-defined values: *Approves of CEO, No opinion of CEO, Disapproves of CEO*
- Contract - The line containing the type of contract: *full-time, part-time, intern.* It also provides information about the length of the contact.
- Pros - Aspects the author likes. Minimum of 5 words
- Cons - Aspects the author likes. Minimum of 5 words
- Advice to management

For the analysis in this thesis, only reviews written in English were scraped. Moreover, I confined myself only to the reviews added by full-time or part-time employees since they represented the vast majority of all records, and intern reviews may have not been entirely comparable or equivalent in weight and detail to reviews of employees with much longer work experience, due to the different nature of an intern's position.

With respect to all the criteria from Sections **3.1** and **3.2**, I gathered the data set of 392,408 reviews for 605 companies in the period of 2 years. For the firms issuing bonds, there were 274,426 records for 350 firms. All the data were scraped with my tool built for this thesis. This web crawler together with its application is thoroughly described in Section **4.1.1**.

Data Analysis

One valuable data insight is that a distribution of a number of reviews strongly varies on the levels across companies, stock markets and market sectors as well. There are 648.60 reviews per company in average with a standard deviation of 1681.00. The selected quantiles are provided below and accompanied by a corresponding histogram depicted in Figure **3.2**.

Quantlies:

- 10th - 39.40
- 25th - 83.00
- 50th - 214.00
- 75th - 559.00
- 90th - 1361.20
- 100th - 27455.00

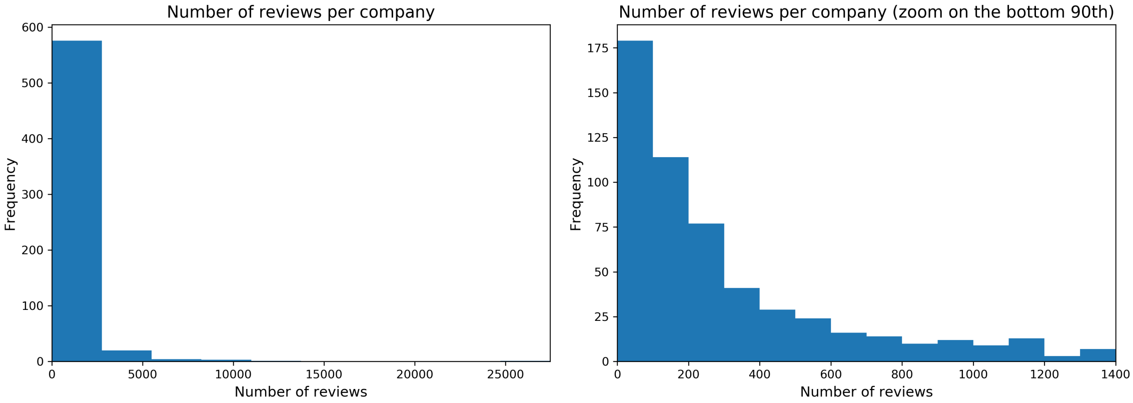


Figure 3.2: Distribution of review

Tables **3.3** and **3.4** then display summary statistics according to the stock market indices and sectors respectively.

Market index	Total	Mean	Std	10th	Q1	Med.	Q3	90th
S&P 500	336,930	713.83	1859.45	44.1	93.0	222.0	588.0	1443.9
FTSE 100	33,497	389.50	698.33	27.0	62.3	134.5	322.3	968.5
EURO STOXX 50	21,973	467.51	772.73	42.2	69.5	190.0	534.5	1043.8

Table 3.3: Number of reviews per company across stock markets

Furthermore, there are differences in the star rating distribution over individual stock market indices and also market sectors. These results are provided in Tables **3.5** and **3.6**. Other tables describing the variation in a higher level of granularity can be found in the Appendix.

Last but not least, it is desirable to point out there are nuances between ratings of full-time versus part-time and current versus former employees. This information can be read from Table **3.7**, where is, among others, a category of 'Not specified' employees, which may be caused by various factors.

- the piece of information regarding the contract and employee relationship is not explicitly displayed alongside a review,

Market sector	Total	Mean	Std	10^{th}	Q1	Med.	Q3	90^{th}
Basic Materials	3,798	122.52	173.51	29.0	47.5	62.0	123.5	237.0
Communications	22,444	680.12	936.59	41.80	73.0	205.0	827.0	2146.8
Consumer Cyclical	92,959	1106.65	3325.23	63.0	111.5	226.5	692.8	1983.9
Consumer Defensive	44,658	858.81	1849.34	49.1	92.3	303.0	630.0	1590.1
Energy	6,742	249.70	338.39	32.0	52.0	105.0	272.5	707.4
Financial Services	59,490	619.69	915.15	57.5	113.5	265.0	609.5	1549.0
Healthcare	31,891	462.19	588.24	72.0	127.0	256.0	587.0	910.0
Industrials	40,102	466.30	627.61	44.0	97.3	259.5	569.8	1032.5
Real Estate	3,552	136.62	227.54	12.0	18.0	72.5	145.0	233.0
Technology	83,958	1216.78	2324.17	62.2	127.0	341.0	1041.0	3641.4
Utilities	2,806	87.69	61.32	30.1	47.0	73.0	104.0	186.8

Table 3.4: Number of reviews per company across market sectors

- errors during parsing textual data from Glassdoor, which can stem from a non-standard formatting for given reviews.

Market index	Mean	Std	Q1	Median	Q3
S&P 500	3.59	1.23	3.0	4.0	5.0
FTSE 100	3.61	1.20	3.0	4.0	5.0
EURO STOXX 50	3.91	1.15	3.0	4.0	5.0

Table 3.5: Descriptive statistics - Ratings across stock markets

Market sector	Mean	Std	Q1	Median	Q3
Basic Materials	3.56	1.23	3.0	4.0	5.0
Communication Services	3.61	1.27	3.0	4.0	5.0
Consumer Cyclical	3.62	1.22	3.0	4.0	5.0
Consumer Defensive	3.40	1.25	3.0	4.0	4.0
Energy	3.66	1.18	3.0	4.0	5.0
Financial Services	3.59	1.20	3.0	4.0	5.0
Healthcare	3.48	1.29	3.0	4.0	5.0
Industrials	3.59	1.27	3.0	4.0	5.0
Real Estate	3.67	1.36	3.0	4.0	5.0
Technology	3.78	1.15	3.0	4.0	5.0
Utilities	3.54	1.31	3.0	4.0	5.0

Table 3.6: Descriptive statistics - Ratings across market sectors

Tables **3.8**, **3.9**, **3.10** show the equivalent statistics to Tables **3.5**, **3.6**, **3.7** (with some additional pieces of information), just confined on the companies issuing bonds within the monitored period. As I have already mentioned, it is obvious there is no chance to conduct any statistically significant analysis for companies listed on FTSE 100 and EURO STOXX 50. Therefore, the analysis of employee sentiment is confined to bonds of companies listed on S&P 500.

Employee	Total ratings	Mean rating	Std	Q1	Med.	Q2
Full-time	316,117	3.63	1.23	3.0	4.0	5.0
Part-time	58,240	3.56	1.17	3.0	4.0	5.0
Not specified	18,043	3.50	1.29	3.0	4.0	5.0
Current	220,135	3.80	1.16	3.0	4.0	5.0
Former	154,224	3.35	1.27	3.0	4.0	5.0
Not specified	18,041	3.50	1.29	3.0	4.0	5.0
Total	392,408	3.61	1.23	3.0	4.0	5.0

Table 3.7: Summary statistics of employee ratings

Market index	Total companies	Total ratings	Mean	Std	Q1	Median	Q3
S&P 500	350	274,426	3.60	1.24	3.0	4.0	5.0
FTSE 100	2	5,341	3.74	1.14	3.0	4.0	5.0
EURO STOXX 50	1	3,235	4.13	1.02	4.0	4.0	5.0

Table 3.8: Descriptive statistics - Ratings across stock markets

Other useful statistics and data insights concerning the Glassdoor data used for this thesis can be found in the Appendix.

Market sector	Total ratings	Mean	Std	Q1	Median	Q3
Basic Materials	2,498	3.60	1.20	3.0	4.0	5.0
Communications	18,781	3.57	1.28	3.0	4.0	5.0
Consumer Cyclical	71,644	3.66	1.21	3.0	4.0	5.0
Consumer Defensive	29,423	3.35	1.26	3.0	4.0	4.0
Energy	3,085	3.61	1.20	3.0	4.0	5.0
Financial Services	43,584	3.59	1.22	3.0	4.0	5.0
Healthcare	25,564	3.44	1.30	3.0	4.0	5.0
Industrials	23,060	3.55	1.28	3.0	4.0	5.0
Real Estate	1,779	3.66	1.42	3.0	4.0	5.0
Technology	61,954	3.76	1.17	3.0	4.0	5.0
Utilities	1,630	3.64	1.31	3.0	4.0	5.0

Table 3.9: Descriptive statistics - Ratings across market sectors

Employee	Total ratings	Mean rating	Std	Q1	Med.	Q2
Full-time	226,117	3.62	1.24	3.0	4.0	5.0
Part-time	43,539	3.57	1.18	3.0	4.0	5.0
Not specified	13,346	3.50	1.29	3.0	4.0	5.0
Current	157,649	3.79	1.16	3.0	4.0	5.0
Former	112,008	3.35	1.27	3.0	4.0	5.0
Not specified	13,345	3.50	1.29	3.0	4.0	5.0
Total	283,002	3.60	1.23	3.0	4.0	5.0

Table 3.10: Summary statistics of employee ratings

Apparently, there are some differences in the distribution of star ratings across stock market sectors. Even more interestingly, the analysis of monthly changes in employee sentiment suggests the sentiment develops non-identically across stock market sectors and stock market indices. This is illustrated by correlation matrices depicted by Figures **3.3** and **3.4**.

Specifically, there are several sectors negatively correlated on FTSE 100 and EURO STOXX 50. It is noticeable that a few sectors exhibiting a negative relation on these two markets, on the other hand, are positively correlated on S&P 500. These detailed correlation matrices can be found in the Appendix.

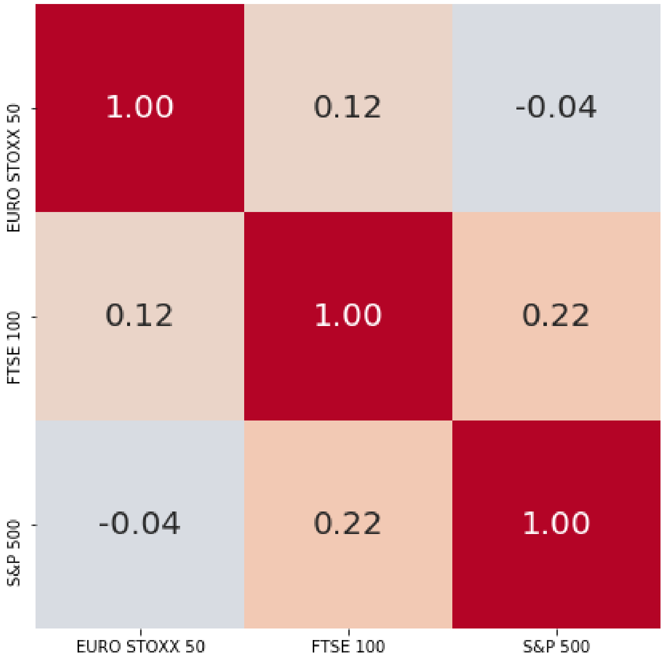


Figure 3.3: Correlation of monthly changes in sentiment across stock markets

3.2.1 Data for fine-tuning

I also had to gather a data set of Glassdoor reviews used for the fine-tuning of BERT. For this purpose, I downloaded a data set with anonymised companies from Kaggle[3]. This provided me with a set of 13,398 examples after cutting the data to have a balanced distribution of positive, neutral and negative reviews. In this case, all reviews with start ratings of 4 and 5 were labelled as positive, records with ratings of 3 were supposed to be neutral, and remaining ones were considered as negative. The data were pre-processed according to the pre-processing methodology summarised in Section **3.4**. Subsequently, they were split into a training and validation set in a ratio of 0.9 to 0.1 respectively.

[3] Data source: www.kaggle.com/fireball684/hackereartherricsson

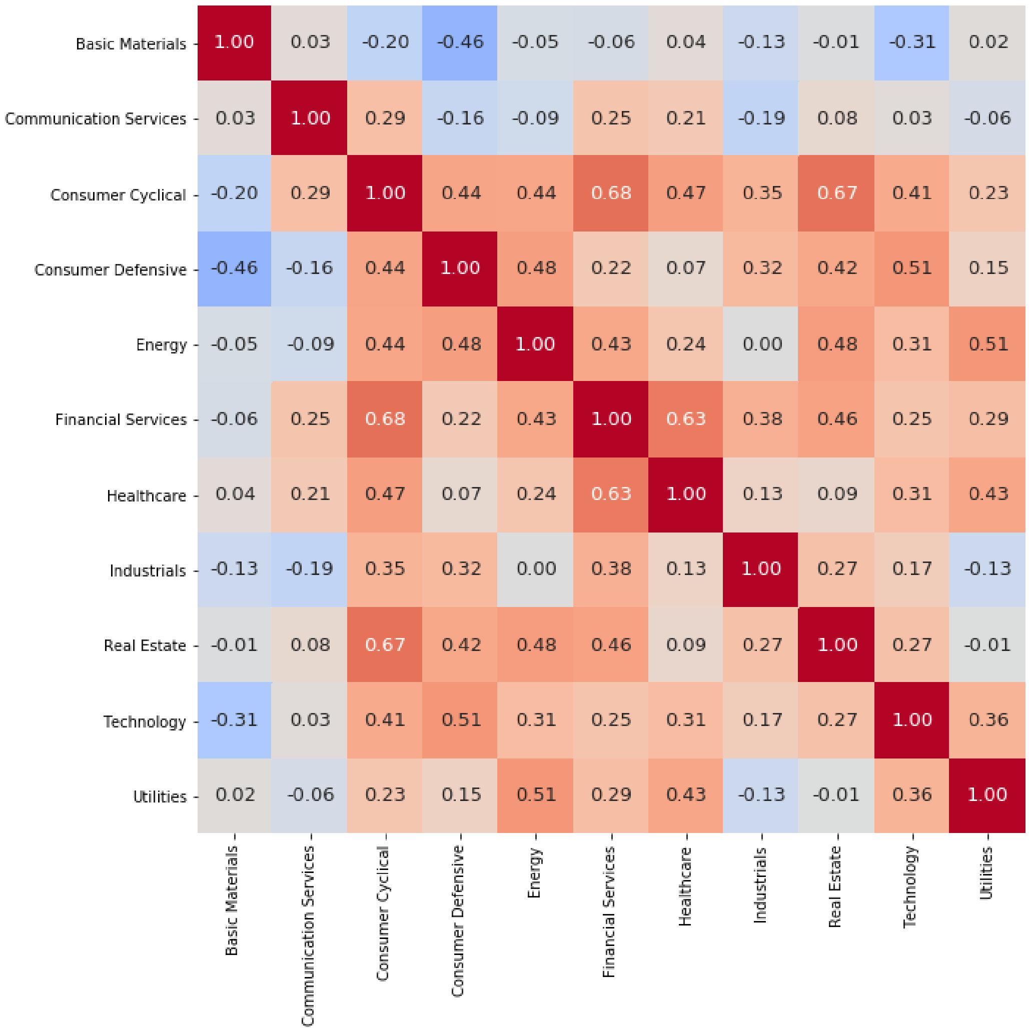


Figure 3.4: Correlation of monthly changes in sentiment across market sectors

3.3 Market Data

This thesis used corporate bond ask and bid prices and interest rate. The source of all these data was Bloomberg and they were retrieved with Bloomberg Terminal software in a combination with *Rblapi*[4], which is the API package for R software. The license necessary for using Bloomberg service was provided by UCL.

In total, I collected 44,044 monthly returns for 2,261 unique corporate bonds issued by companies listed on S&P 500. These data were retrieved using a ”lookup” function integrated in Bloomberg Terminal, which were not able to reach already maturated bonds. Some bonds may have also been omitted due to the presence of the limit imposed on search results[5]. For further studies, it would thus be more beneficial to use some licensed data to cover the larger

[4] https://cran.r-project.org/web/packages/Rblpapi/Rblpapi.pdf

[5] Only 20 searches are displayed for each query

scope of corporate bonds.

3.4 Data Pre-Processing

3.4.1 Employee Sentiment Data

In this thesis, no pre-processing of the employee ratings was conducted as they were not fed into any algorithm requiring standardised data. Therefore, it was permissible to leave ratings ranging from 1 to 5. On the other hand, there was a necessity to transform reviews so that they can be read by BERT. For this purpose, the reviews had to be tokenised at first. In this project, the pre-trained '*bert-base-cased*' tokeniser delivered by Hugging Face was used.

As some reviews were too long, it was beneficial to set a maximum length and cut those exceeding this limit. This step is, in general, appropriate because shortening a small fraction of sequences resulted in losing only a tiny amount of information while training and evaluation time is considerably reduced. The maximum length of 80 words was used in this study.[6]

After this procedure, a token <CLS> had to be added before each review. This was done so that the language model would be able to distinguish which down-stream task should be done. Furthermore, each sequence was appended with a token <SEP> that determined the end of that sequence.

As all input sequences must be of the same length, all of them were padded with respect to the length limit. This was achieved by adding <PAD> tokens in a combination with generating an attention mask. Generally, this mask is represented by a vector of ones and zeros, which is an indication for BERT which input tokens should be used for loss calculation and subsequent optimisation.

Finally, both arrays, the tokenised input and attention mask, were transformed to the PyTorch tensor, which is a standardised input type format used for deep learning models built with *PyTorch*[7].

3.4.2 Market data

For the purpose of simplicity, the monthly return on the corporate bond was calculated as

$$R_t = \frac{Ask\_price_t - Ask\_price_{t-1} + Interest}{Ask\_price_{t-1}},\ t = 2, ..., T, \tag{3.1}$$

when bonds are longed, and

$$R_t = \frac{Bid\_price_{t-1} - Bid\_price_t - Interest}{Bid\_price_{t-1}},\ t = 2, ..., T, \tag{3.2}$$

[6] This threshold was set based upon my observations

[7] Deep learning library; www.pytorch.org/

if they are shorted. Furthermore, when the bonds performance was trailed over past 3 months for determining the momentum, the return was determined as

$$R_t = \frac{Price_{t-3} - Price_t}{Price_{t-3}},\ t = 4, ..., T, \tag{3.3}$$

where $Price_t$ was computed as a mean value of bid and ask prices.

While this approach does not perfectly reflect the methodology of how corporate bond returns are calculated, it should provide us with sufficient evidence whether the proposed sentiment factor for the bond trading gives any meaningful signal. On the other hand, this can lead to overestimating portfolios returns as, for example, transaction costs are neglected, which is discussed in the discussion Chapter **6**.

4. Methodology

This chapter consists of five parts. First, it presents scraping tools devised for gathering data from Glassdoor and Yahoo Finance. Subsequently, it provides an outline of the retrieval pipeline and database. A description of different approaches for scoring employee sentiment and incorporation of these analysis results into the multi-factor model follow. The closing section covers test methodology.

4.1 Tools Developed for Data Retrieval

Two different scraping tools were developed for this thesis. First, the *selenium*-based[1] web crawler for automated browsing through Glassdoor and parsing of employee reviews. Second, a relatively simple program based on standard Python HTTP and parsing libraries, *requests*[2] and *Beautiful Soup*[3], which is intended for getting information from Yahoo Finance. The latter one is also capable of downloading auxiliary data from Wikipedia.

Both scrapers are designed to store the acquired data set either as a CSV/Excel file, or in a database created with SQL statements generated with another Python package, *Django*[4].

4.1.1 Glassdoor Scraper

Due to a design of the Glassdoor web pages, the scraper incorporates multiple components that are briefly described in the **Components** subsection below. Everything is accompanied by supportive justifications, illustrations and code snippets. All the code presented in this section is a part of my own work. The high-level application of this tool is then presented in the **Application** subsection.

Since browsing the Glassdoor website requires user interaction, it is necessary to use a browser automation library such as *Selenium*. This enables us to build a robot that goes through web pages and interacts with them like a human does, but in an almost completely automatic way.

[1] pypi.org/project/selenium
[2] pypi.org/project/requests
[3] pypi.org/project/beautifulsoup4
[4] pypi.org/project/Django and docs.Djangoproject.com/en/3.1

It is important to mention that libraries such as *selenium* usually require a web driver for their full functionality. This thesis relies on *ChromeDriver*[5].

Before diving into the individual components of scraper, I would like to introduce the whole scraping process briefly. The bot needs to handle following tasks:

1. signing in to a Glassdoor account,
2. finding the first review page of a company,
3. unrolling all reviews exceeding a certain length on the page,
4. scraping all reviews on the page,
5. moving on to the next page for the company,
6. repeating steps 3 to 5 until the last page containing reviews is reached. Then, terminate scraping and start with another company.

During the process outlined above, the program is required to locate various elements in the web page HTML. These functions used for this task are, therefore, introduced at this place so that they can be easily referenced later in the text. Let import and initialised methods and classes. The class ”webdriver.Chrome(**args)”, where **args represents argument options, offers following functions available for detecting various content.[6]

```
from selenium import webdriver
driver = webdriver.Chrome(**args)
```

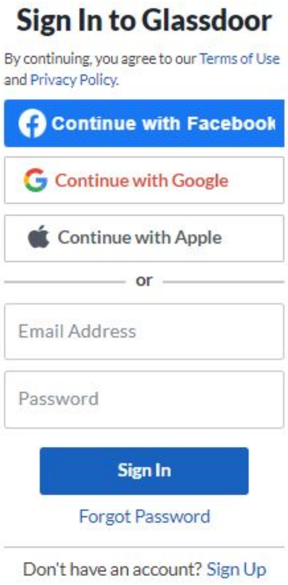
Code Snippet 4.1: Import web driver module

- ”find_element_by_class_name”
- ”find_element_by_id”
- ”find_element_by_name”
- ”find_element_by_xpath”

The choice of a strategy using for locating elements hinges on the convenience of a given solution. In other words, it depends on the programming style. In some cases, it is possible to locate elements with more than one choice, sometimes a coder is enforced to stick to an only available option.

[5] chromedriver.chromium.org

[6] The list below contains only the methods used in this project. There are other functions, which can be found at www.selenium-python.readthedocs.io/locating-elements.html. The attributes follow an HTML convention.



Sign In to Glassdoor

By continuing, you agree to our Terms of Use and Privacy Policy.

Don't have an account? Sign Up

Figure 4.1: Glassdoor - Login portal
Source: Glassdoor

Components

Surfing the Glassdoor websites needs a user or a robot to be signed in so that reviews in the full scope will be available. The first crucial component of the scraper is then responsible for logging in with user credentials. The login portal is portrayed in Figure **4.1**, and a corresponding high-level source code handling all necessary actions is provided in Code Snippet **4.2**.

```
from selenium import webdriver
driver = webdriver.Chrome(**args)
## code continues... ##

driver.find_element_by_name('username').send_keys(<email>)
driver.find_element_by_name('password').send_keys(<password>)
driver.find_element_by_xpath('//button[@type="submit"]').click()
```

Code Snippet 4.2: Glassdoor - Login

As personal data, including an e-mail and a password, are not appropriate for storing in the source code, the better practice is to create a separate JSON[7] file. This file, which contains such sensitive information, is then opened and parsed directly within the main file. This procedure is also followed in this work.

Another step in getting employee reviews is to search for a company we are interested in. In

[7] json.org

general, there are two main ways to do this.

1. A user-friendly approach is to find a firm by inserting its name into the company search on the web pages (see Figure **4.2**). However, this method was not used because it proved to be quite unstable, as the bot was often re-routed to URLs that cannot be loaded. Moreover, more than one company can be found with the same name, therefore, reviews for an incorrect firm can be unintentionally scraped.

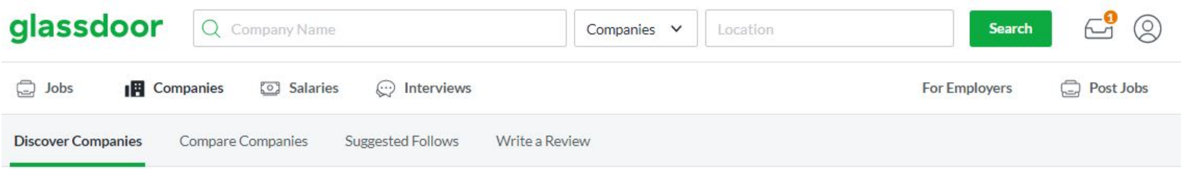


Figure 4.2: Glassdoor - Company search
Source: Glassdoor

2. The alternative is to manually find a URL address to the first page of reviews for the required company. While this method is less comfortable since it requires the user to find these URL links manually, it is much faster and reliable in general than the first approach.

Once the page with reviews for a given company is obtained, the reviews, by default, are sorted by the popularity of individual records. This is not the most desirable option when one wants to scrape records over a certain time period without handling a number of reviews out of that time range. It is thus more efficient to order the reviews by date. This can be easily achieved by appending to the URL address the following statement "sort.sortType=RDsort.ascending= false".

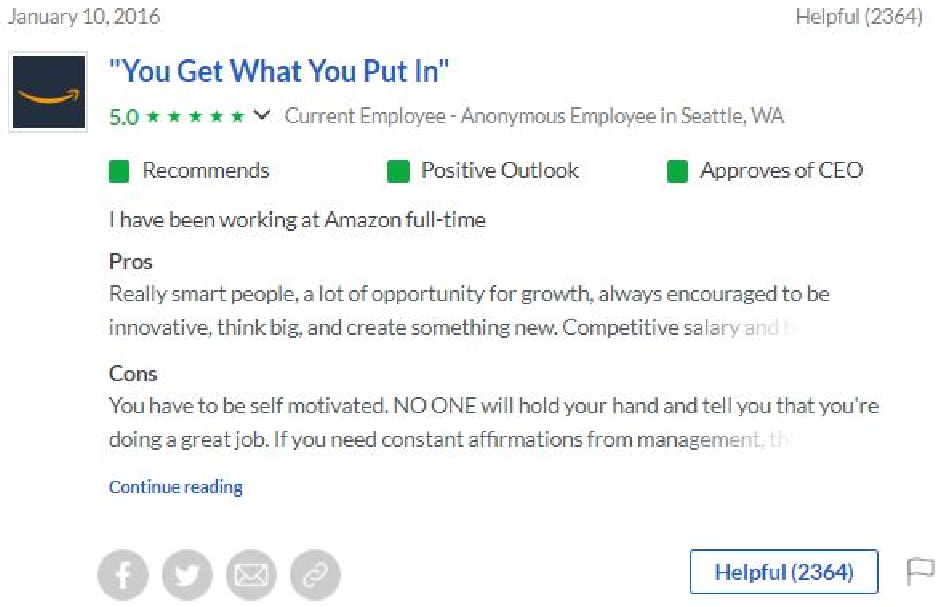
The cornerstone of crawling through the Glassdoor web pages lies in unrolling reviews by clicking on the "Continue reading" button (see Figure **4.3**), which is located at the bottom of most reviews exceeding a certain length. Without clicking on "Continue reading" (when present), it is impossible to retrieve the full text of the review from the HTML code. After scraping a review, it takes about 1.5-2.5 seconds for the website to refresh and for another clicking element (for the next review) to become available. This idle period may sometimes even prolong, which is why an error handling mechanism is desired, which is implemented as shown in (pseudo) Code Snippet **4.3**. For this error handling, it is more efficient to loop over shorter breaks rather than a single longer one because the second option might impede the speed of scraping.

As soon as the reviews are unrolled, particular elements, described in Section **3.2**, from individual posts can be parsed. This is achieved with *re*, a standard python module. Since this procedure consists of multiple functions built using a few simpler functions, covering all the details is beyond the scope of this report. The source code can be found in the cited

```
import time
success = 0

while success == 0:
    try:
        driver.find_elements_by_xpath(<`Continue reading` path>)[0].click()
        success += 1
    except:
        time.sleep(0.5)
```

Code Snippet 4.3: Glassdoor - Continue reading



January 10, 2016 Helpful (2364)

"You Get What You Put In"

5.0 ★★★★★ Current Employee - Anonymous Employee in Seattle, WA

🟩 Recommends 🟩 Positive Outlook 🟩 Approves of CEO

I have been working at Amazon full-time

Pros

Really smart people, a lot of opportunity for growth, always encouraged to be innovative, think big, and create something new. Competitive salary and b

Cons

You have to be self motivated. NO ONE will hold your hand and tell you that you're doing a great job. If you need constant affirmations from management, th

Figure 4.3: Glassdoor - 'Continue reading' button
Source: Glassdoor

GitHub repository.

The last step ensuring smooth operation of the tool is to stop scraping when a page with no review is reached, which is possible on Glassdoor. To avoid browsing empty pages indefinitely, we can simply count reviews on a page and terminate if desired (see Code Snippet **4.4**).

Application

Notwithstanding the complexity of the scraper itself, its use is pretty simple, and everything can be executed from a terminal. Furthermore, the scraper allows for direct specification of various optional parameters. The simplest application of my tool can be illustrated with the Code Snippet **4.5**.

This command runs scraping from the main file. First, "chrome_drive_path" is necessary

```
reviews = driver.find_elements_by_xpath('//li[@class="empReview cf"]')
reviews.extend(driver.find_elements_by_xpath(
    '//li[@class="noBorder empReview cf"]'))

if len(reviews) == 0:
    `TERMINATE SCRAPING`
```

Code Snippet 4.4: Glassdoor - Counting reviews on a single page

to specify as a web driver constitutes an essential component of scraper. Credentials are represented by a JSON file containing a user e-mail and password. Company names along with corresponding URL links are fed through two text files. These can be generated from an Excel/CSV sheet with another python application in the repository. The last two arguments, "min_date" and "mysite_path", specify the latest date of review, we desire to obtain, and a path to a Django application defining our database respectively.

```
python main.py  --chrome_driver_path '/mnt/c/data/chromedriver/'
                --credentials '/mnt/c/data/credentials.json'
                --companies '/mnt/c/data/companies.txt'
                --url '/mnt/c/data/urls.txt'
                --min_date '2018-06-30'
                --mysite_path '/mnt/c/mysite'
```

Code Snippet 4.5: Glassdoor scraper - application

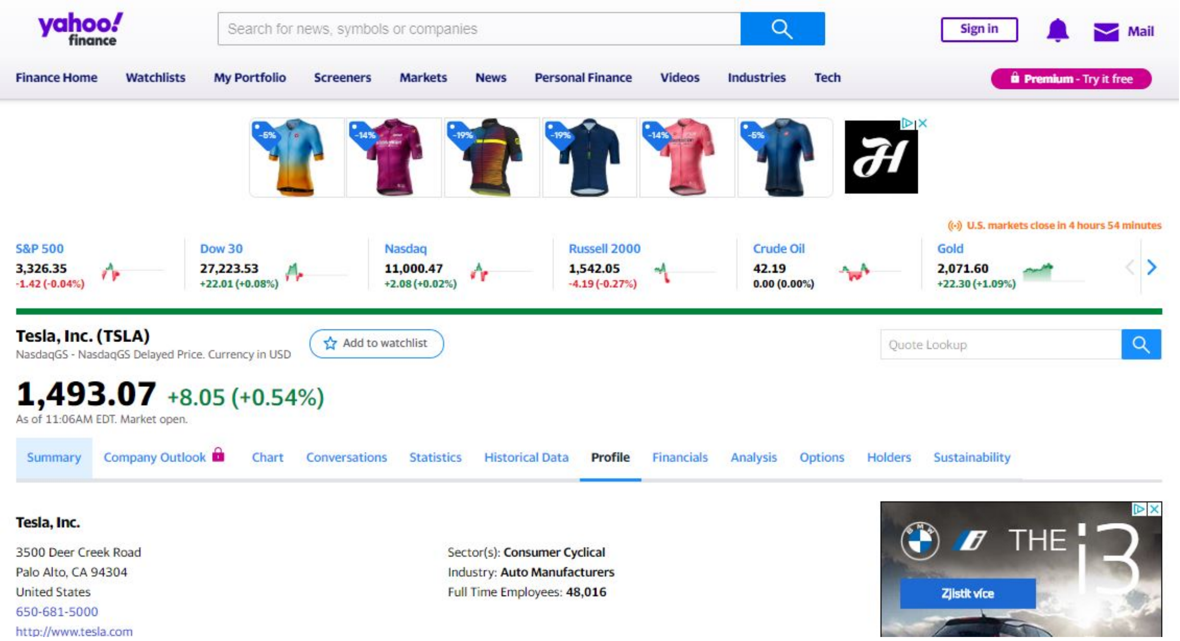
Other optional parameters with corresponding documentation can be found in the README.md file stored in the GitHub repository of this thesis.

4.1.2 Yahoo Scraper

Yahoo scraper tailored for this work is conceptually significantly lighter compared with the Glassdoor tool described above. This is owed to the availability of all necessary information immediately after loading of a company's web page. Thus it is not necessary to build a bot interacting with a website. This program is, therefore, built with well-known python modules, *requests* and *BeautifulSoup*. The former packages are used for obtaining the HTML source code and the latter one for parsing text.

All the pieces of information, that are used in this work, are retrievable from two sections - Profile and Financials (see Figure **4.4**). These sections are easily accessible for all companies listed on any stock exchange because of a generic form of the URL address as shown in Code Snippet **4.6**.

The stock indices can be either gathered manually, or, alternatively, Yahoo Scraper has a built-in feature, which can download indices for stocks listed on S&P 500, FTSE 100 or EURO STOXX 50 indices from Wikipedia. This Wikipedia crawler works similarly to the



U.S. markets close in 4 hours 54 minutes

S&P 500	Dow 30	Nasdaq	Russell 2000	Crude Oil	Gold
3,326.35	27,223.53	11,000.47	1,542.05	42.19	2,071.60
-1.42 (-0.04%)	+22.01 (+0.08%)	+2.08 (+0.02%)	-4.19 (-0.27%)	0.00 (0.00%)	+22.30 (+1.09%)

Tesla, Inc. (TSLA)
NasdaqGS - NasdaqGS Delayed Price. Currency in USD

1,493.07 +8.05 (+0.54%)
As of 11:06AM EDT. Market open.

Tesla, Inc.

3500 Deer Creek Road
Palo Alto, CA 94304
United States
650-681-5000
http://www.tesla.com

Sector(s): Consumer Cyclical
Industry: Auto Manufacturers
Full Time Employees: 48,016

Figure 4.4: Yahoo Finance
Source: Yahoo Finance

```
url = f'https://finance.yahoo.com/quote/{<stock>}/{<section>}?p={<stock>}'
```

Code Snippet 4.6: Generic form of Yahoo Finance URL

Yahoo one because all the data are obtainable directly from the first loading of the page. This program is, therefore, built using a combination of *requests*, *BeautifulSoup* and *re* modules. The last one helps with the text parsing. Getting data from Wikipedia is the least difficult out of all three cases described, as all the data are well formatted in tables.

Application

Similarly to the application of Glassdoor crawler, this program can be again directly executed from a terminal. A possible application is in Code Snippet **4.7**.

```
python main.py --stock_indices 'S&P 500 | FTSE 100 | EURO STOXX 50'
               --mysite_path '/mnt/c/mysite'
```

Code Snippet 4.7: Yahoo and Wikipedia scraper - application

This command first runs the Wikipedia scraper and gets all companies (with their stock symbols) currently listed on S&P 500, FTSE 100 and EURO STOXX 50. These data are temporarily stored in the scraper *object*. Subsequently, information about firms are gathered from Yahoo Finance and the individual records are immediately pushed to the *Django* database.

4.2 Database and Pipeline

The backbone of the database consists of two interconnected tables, which are administrated by *Django* and proved to be working with *SQLite*[8] or *MySQL*[9] databases at the back-end. For the projects of lower scale, *SQLite* is completely sufficient. Furthermore, there is no need for running the database on a server when *SQLite* is used. Therefore, this project is based on *SQLite*.

The only limitation of *SQLite* is an impossibility of concurrent writing into the database. Importantly, attempting to simultaneously write into the database is not prevented by *SQLite*. It is, therefore, completely on the users of the software to make sure there are no events of concurrency. If this paradigm is not obeyed, *SQLite* will not be able to handle this order, which will result in the corruption of the whole database. While there are techniques for repairing such corrupted files, there is still a non-negligible danger of losing the whole work.

The two tables that constitute the database here are intended for storing companies' information (*Company* model) and employee reviews (*Review* model) respectively. These tables are created with the *Django* class *models.Model* which is responsible for generating database queries. This object consists of one or more fields that represent column names in the output table. There are multiple standard field formats supported by *Django*[10], and all of them are rooted at *django.db.model*. This project works with the following ones.

- CharField
- IntegerField
- FloatField
- TimeField
- ForeignKey - The field representing a many-to-one relation, i.e. various inputs in one table are strictly linked to the one record in the other one.

The items above usually require the setting of a few parameters. Individual fields have been, therefore, initialised as shown in Code Snippets **4.8**. The concrete *models.Model* schemes implemented in this project can be found in the Appendix.

First, the parameter *max_length* determines the maximum length of character input. Another one, *blank*, allows the insertion of an empty string, which is an alternative for the *null* value in case of integers and floats. The argument *unique* ensures each company occurs exactly once in the *Company* table. Insisting on unique records is necessary since the connection with the other table through *models.ForeignKey* would not be working otherwise. The last yet covered parameter is *on_delete* that specifies an action to take with records if their superordinate is

[8] www.sqlite.org/

[9] www.mysql.com/

[10] All of them can be found at docs.djangoproject.com/en/3.1/topics/db/models/

```
from django.db import models
max_length=<max_length>

class Company(models.Model):
    company = models.CharField(max_length=max_length, blank=True, unique=True)

    def __str__(self):
        return self.company

class Review(models.Model):
    entityField = models.ForeignKey(to=Company, on_delete=models.CASCADE)
    characterField = models.CharField(max_length=max_length, blank=True)
    integerField = models.IntegerField(null=True)
    floatField = models.FloatField(null=True)
    timeField = models.TimeField(null=True)

    def __str__(self):
        return self.characterField
```

Code Snippet 4.8: Django Model - Class instantiation

deleted. An option *models.CASCADE* enforces all subordinates entries to be removed with their superordinates. Finally, an inner function *__str__(self)* defines the value to be printed in the database overview.

Since the *Review* model depends on the *Company* one, users have to build the latter table first. The ultimate structure is resembled with Figure **4.5**. My system, moreover, ensures the uniqueness of *Review* and *Company* records. This is attained by scanning a database for an input to save, and the new record is pushed in if and only if the same record does not exist, as shown in Code Snippet **4.9**, where *args contains values for the model's fields.

4.3 Sentiment Analysis

In this thesis, sentiment analysis is used as a tool for analysing employees' opinions about their company. I, therefore, calculate sentiment proxied by either star ratings or reviews retrieved from Glassdoor for a company. The sentiment scores are calculated in rolling time windows, which are covered in Subsection **4.3.2**.

Generally, the sentiment score for company i at some time period j is given as

$$\text{Sentiment}_{ij} = \frac{\sum_{k=1}^{N_{ij}} w_k^{(ij)} \cdot r_k^{(ij)}}{\sum_{k=1}^{N_{ij}} w_k^{(ij)}},\ k = 1, ..., N_{ij}, \tag{4.1}$$

where N_{ij} is the total number of reviews for company i at time period j. $r_k^{(ij)}$ denotes either a star rating, ranged from 1 to 5, or probability of a review being positive, when reviews are used. The probability that the given review being positive is returned by the language model BERT. $w_k^{(ij)}$ represents a weight of a given rating or a review, which is again further described in Subsection **4.3.2**.

```
from MyDjangoModels import Review
def checkIfRecordExists(record):
    try:
        Review.objects.get(*args)
        return True
    except Company.DoesNotExist:
        return False

def writeRecord(record):
    if not checkIfRecordExists(record):
        reviewRecord = Review(*args)
        reviewRecord.save()
    else:
        pass
```

Code Snippet 4.9: Django - Writing a record if it does not already exist

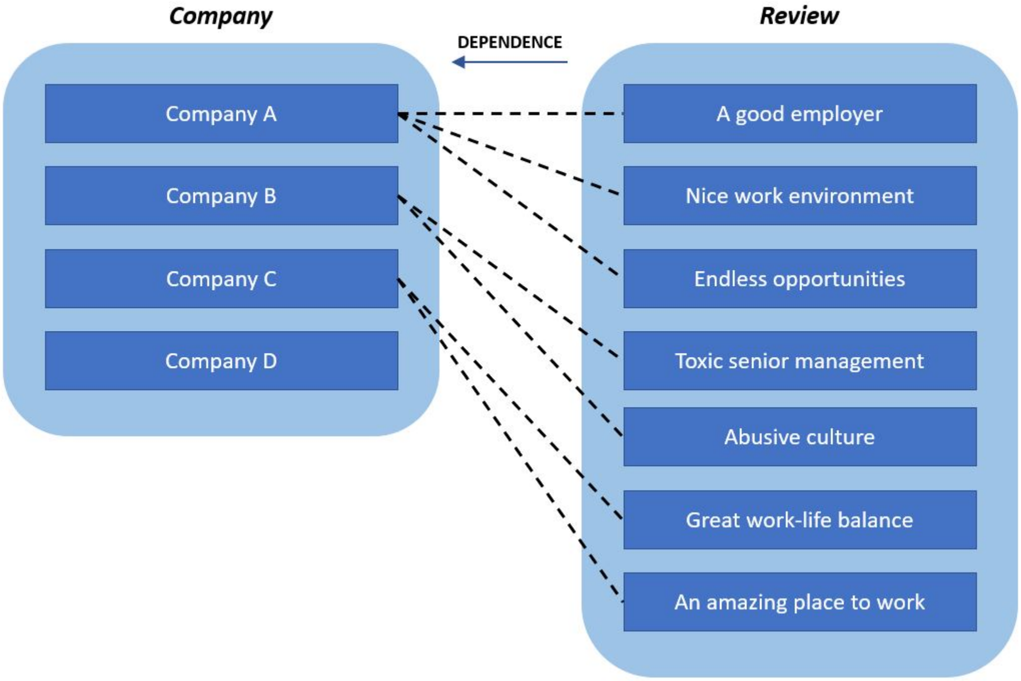


Figure 4.5: Django - Database structure

4.3.1 BERT Implementation

In this thesis, BERT is used as a language model to estimate the probability of a review being positive. Each review consists of two concatenated parts, pros and cons. To make reviews of a suitable format for the model, they must be first padded to the same length. Moreover, special tokens must be attached and attention mask needs to be generated as described in Section **3.4**. All these steps can be easily done with a pre-trained tokeniser delivered by Hugging Face. The transformed input can be, therefore, directly obtained with a few lines of codes.

```
from transformers import BertTokenizer
tokenizer = BERT.from_pretrained('bert—based—cased')
transformed_review = tokenizer.encode_plus(
    review,
    max_length=max_length,
    truncation=True,
    add_special_tokens=True
    pad_to_max_length=True,
    return_attention_mask=True
    return_tensors='pt'
)
```

Code Snippet 4.10: BertTokeniser - Review transformation

Once the input is transformed, it can be directly passed to the BERT model tailored for sentiment analysis. The architecture of the model used in this Masters project can be summarised as follows:

$$\text{Model} = \{\text{BERT} \rightarrow \text{DROPOUT} \rightarrow \text{FULLY-CONNECTED}\}.$$

Here, the base version of BERT is used (the model with 12 hidden layers with an embedding size of 768 units and the 12-head attention). After this block, a dropout layer, with a dropout probability of 0.3, is implemented to regularise our model. Finally, a fully-connected layer, followed by a softmax function, is placed. The output of this whole model is then represented with a vector of size 3.

$$\text{Model(review)} = \begin{bmatrix} \text{Prob. of being positive} \\ \text{Prob. of being neutral} \\ \text{Prob. of being negative} \end{bmatrix} = \begin{bmatrix} p^{+} \\ p^{0} \\ p^{-} \end{bmatrix} \tag{4.2}$$

Since the ultimate, fully-connected layer needs to be trained, the model is fine-tuned with all weights being frozen except for the ones in the very last layer. The fine-tuning is conducted with the following parameters, which follow the recommendations of Devlin et al. (2018).

- Objective: Minimisation of cross-entropy loss

- Number of epochs: 4
- Batch size: 32
- Optimiser: AdamW
- Learning rate: $4 \cdot 10^-5$

The whole model is written in *PyTorch*[11]. Besides, Hugging Face's implementations of the pre-trained BERT and AdamW are used. Moreover, the model and the corresponding definitions of a training and validation step and epoch are wrapped with *PyTorch Lightning*[12]. Encapsulation with this high-level library brings a couple of advantages. First, it allows a programmer to avoid a lot of boilerplate code and thus makes the script more readable for other developers. Second, the code for the model and its optimisation is completely identical regardless of device (i.e. CPU, GPU, TPU) used for a computation. These two points combined together further implies explicitly allocation of *PyTorch* models and tensors to a device within a script is no more necessary as *PyTorch Lighting* handles this job on itself.

4.3.2 Approaches to Employee Sentiment Scoring

The sentiment score is evaluated either based on employees' ratings or reviews. There are following three approaches tested in this thesis.

1. **Ratings** - The simplest method for determining sentiment score for a given company i in period j is to calculate this metric directly on the star ratings. In this case, each record has the same weight. Equation (**4.1**) can be, therefore, simplified as

$$\text{Sentiment}_{ij} = \frac{\sum_{k=1}^{N_{ij}} r_k^{(ij)}}{N_{ij}}. \tag{4.3}$$

2. **Unweighted reviews** - Another approach uses reviews as a proxy to calculate sentiment score. On this occasion, each review is scored with BERT. The sentiment of an individual review is defined as

$$\text{sentiment}(\text{Model}(\text{review}_k^{(ij)})) = p_k^+ - p_k^-,\ k = 1, ..., N_{ij}, \tag{4.4}$$

where p_+ and p_- are output probabilities of the language model. In this study, the additive method is preferred to the ratio one, i.e.

$$\text{sentiment}(\text{Model}(\text{review}_k^{(ij)})) = \frac{p_k^+}{p_k^-},\ k = 1, ..., N_{ij}, \tag{4.5}$$

because the latter one can generate undesirable outliers in the data if the review is as-

[11] www.pytorch.org
[12] www.pytorch-lightning.readthedocs.io

signed with a very high probability, close to 1, to be positive, and a very low probability, close to 0, to be negative (or also vice versa). On the other hand, formula from equation (**4.4**) ensures

$$\text{sentiment}(\text{Model}(\text{review}_k^{(ij)})) \in [-1, 1]. \tag{4.6}$$

I also include both positive and negative probabilities, p_k^+, p_k^-, because disregarding, for example, p_k^- from equation (**4.4**) leads to the losing of information about whether the model returns a higher probability the review being neutral or negative. It would have resulted in an ambiguity like

$$r_1^{ij} = \begin{bmatrix} 0.3 \\ 0.65 \\ 0.05 \end{bmatrix} = \begin{bmatrix} 0.3 \\ 0.05 \\ 0.65 \end{bmatrix} = r_2^{ij}, \tag{4.7}$$

which is, of course, an undesired information loss.

Finally, the sentiment for the whole company in an observed time frame is then again calculated as in (**4.3**) with $r_k^{(ij)}$ being given as

$$r_k^{(ij)} = \text{sentiment}(\text{Model}(\text{review}_k^{(ij)})) = p_k^+ - p_k^-, \; k = 1, ..., N. \tag{4.8}$$

3. **Weighted reviews** - The last investigated method further takes the length of reviews into consideration. The review length is measured by its total number of words, and represents the weight of a review in (**4.1**). An aggregated sentiment score can be thus expressed with the following formula

$$\text{Sentiment}_{ij} = \frac{\sum_{k=1}^{N}(\text{review\_length}_k^{(ij)}) \cdot r_k^{(ij)}}{\sum_{k=1}^{N} \text{review\_length}_k^{(ij)}}. \tag{4.9}$$

The sentiment scores are calculated in one-month and three-month periods, starting with the beginning of a calendar month. Furthermore, time series of month-to-month changes in sentiment score are also computed, and used as a bond performance indicator.

4.4 Proposed Factor Model

The proposed model is conceptually similar to those presented in Section **2.1** (Factor Investing in the Corporate Bond Market). In order to construct the full long-short portfolio, we build long and short decile portfolio with respect to the companies' sentiment factor, which is calculated according to the methodology in Section **4.3**. In this case, a definition of a decile portfolio slightly differs from the one normally used when top and bottom 10 per cent of bonds are picked to be long-bought and short-sold, respectively. In my case, top and bottom companies instead of bonds are selected with respect to the sentiment factor. This sorting is also done as the first step in the bond selection process.

Since there is usually more than one type of a bond per company, as the firm may issue debt securities with different maturities etc., another ordering rule is desirable to introduce in order to avoid buying or selling all types of bonds issued by picked companies. In this thesis, the low-risk factor is arbitrary chosen as an auxiliary characteristic for sorting the bond universe. Recalling a definition of the low-risk factor, the bond with the shortest maturity is picked to buy and the longest-maturity debt security is to be sold for top and bottom companies, respectively.

I introduced that additional measure for the bond selection in order to cap investor's exposure to the individual firms. I also assume it would be unreasonable to buy and short all types of bonds issued by the selected top and bottom companies without further consideration of their performance.

4.5 Test Methodology

For the testing of the efficacy of the employee sentiment factors, mean monthly returns on the portfolios are calculated. The monthly return on a bond in the portfolio follows the data pre-processing from Section **3.4**, i.e.

$$R_{l,t} = \frac{Bid\_price_{l,t} - Bid\_price_{l,t-1} + Interest_l}{Bid\_price_{l,t-1}}, \; l = 1, ..., |L_t|, \; t = 1, ..., T \tag{4.10}$$

if the bond is longed, and

$$R_{l,t} = \frac{Ask\_price_{l,t-1} - Ask\_price_{l,t}}{Ask\_price_{l,t-1} - Interest_l}, \tag{4.11}$$

if it is shorted. In equations (**4.10**) and (**4.11**), l denotes bond l from the pool of all bonds of size L_t available to trade at time t. Again, this definition of bond returns is rather simplified as it neglects elements such as compound interest or transaction costs (the latter one might be cumbersome to estimate). Furthermore, monthly interest payments are assumed to be held for the purpose of simplicity.

The return on the whole portfolio is then calculated as an arithmetic mean, i.e.

$$R_t = \frac{\sum_{l \in \mathcal{B}_t} R_{l,t}}{|\mathcal{B}_t|}, \; t = 1, ..., T \tag{4.12}$$

where $\mathcal{B}_t$ denotes indices of bonds chosen for the portfolio at time t. The arithmetic mean is used because only unweighted bond portfolios are considered. This means each bought or sold bond is assumed to have the same weight in the portfolio.

Even though the definition of returns are simplified, and thus does not have to perfectly match the reality, I believe it can still provide us with a valuable insight whether the utilisation of employee sentiment is useful in picking good and poor performing bonds respectively. The holding period for all bonds is one calendar month. The formation period is determined according to the length of time frame used for the sentiment score calculation highlighted in Section **4.3**, i.e.

- one month,
- three months.

The results of this analysis are further compared with the returns of low-risk and momentum-based portfolio, which are used as a baseline. In this case, the holding period is again one month and the formation period lasts three months for the momentum approach.

Besides mean returns, standard deviation is also computed so that we can test the returns for statistical significance. For this purpose, I calculate t-value

$$|t\text{-value}| = \left| \frac{\bar{R}}{\sqrt{\frac{\sum_{t=1}^{T}(R_t-\bar{R})^2}{T-1}/T}} \right|, \tag{4.13}$$

where $\bar{R}$ denotes the mean monthly return. Finally, t-value together with a degree of freedom, which equals T[13], is used for obtaining p-value.

Moreover, correlation among sentiment-based and momentum-based portfolios are investigated. In this case, I use the Pearson's correlation coefficient

$$\rho_{ij} = \frac{\sum_{t=1}^{T}(R_t^S - \bar{R}^S)(R_t^M - \bar{R}^M)}{\sqrt{\sum_{t=1}^{T}(R_t^S - \bar{R}^S)^2 \cdot \sum_{t=1}^{T}(R_t^M - \bar{R}^M)^2}}. \tag{4.14}$$

In the equation above, R^S and R^M corresponds to the sentiment-based and momentum-based portfolio returns, respectively.

[13] T is the total number of portfolio month returns, thus it gives us the number of observations. Importantly, I assume monthly returns to be independent according to the efficient-market hypothesis (Fama, 1970).

5. Employee Sentiment in Generating Return

This chapter first evaluates an incorporation of a factor, derived from star ratings as a proxy for sentiment, into the factor model and its ability to generate return. Subsequently, this technique is compared with the model utilising factors that are derived from different NLP sentiment scoring methods. The results are studied against the returns of momentum- and low risk-based portfolios. This study suggests that taking employee sentiment into account enhances portfolio returns compared with the low-risk portfolios while keeping risk (measured by variance) relatively low with respect to the momentum portfolios.

The experiments according to the methodology described in Sections **4.4** and **4.5** were run and the results are summarised in Sections **5.1** and **5.2**. In all experiments below, the following notation is used.

- **1M** - Employee sentiment calculated as a month average;
- **Δ1M** - Month-to-month change in **1M** employee sentiment;
- **3M** - Employee sentiment calculated as mean over three calendar months;
- **Δ3M** - Monthly change in **3M** employee sentiment;
- **Low risk** - Bonds are chosen using a simplified low-risk strategy, i.e. bonds with the shortest maturity are long-bought and one with the longest are short-sold;
- **Momentum** - Bonds are chosen using a momentum-based strategy.

Furthermore, as suggested in Section **3.2**, the results are presented only for S&P 500. The reason is that an analysis for companies listed on the other two indices, FTSE 100 and EURO STOXX 50, is inadequate due to the woefully few companies I was able to collect bond data for.

5.1 Star Ratings

The returns on portfolios based on ratings, low risk and momentum are summarised in the tables below. In all cases, the holding period of 1 month was used.

	1M	**Δ1M**	**3M**	**Δ3M**	**Low risk**	**Momentum**
Mean return	-0.37 %	-0.33 %	-0.33 %	-0.24 %	-0.35 %	0.08 %
St. dev.	1.19%	1.14 %	1.35 %	1.62 %	2.19 %	2.74 %
|t|	1.43	1.34	1.11	0.68	0.72	0.13
p-value	0.17	0.20	0.28	0.50	0.48	0.90
Annualised return	-4.36 %	-3.93 %	-3.85 %	**-2.87 %**	-4.07 %	**0.92 %**

Table 5.1: Returns of the long-short portfolios (ratings); T=21 (number of monthly returns)

Table **5.1** depicts the results on the long-short portfolios using the star ratings. In this case, all the returns are negative, which might be disappointing. However, if one focuses only on the the returns of the long portfolios, a significant improvement can be observed (see Table **5.2**). It, therefore, seems there is a flaw in a short strategy.

Regarding the long-short portfolios and ignoring the absolute term, we can still compare the performance of individual strategies relatively. Even though all sentiment-based portfolios generate worse returns than the momentum-based one, they exhibit considerably lower variance. It can be also recognised that the strategies based on month-to-month changes, instead of absolute sentiment score, tend to perform better. Furthermore, a longer formation period looks to be beneficial as well. The mean monthly return of the **Δ3M** strategy is higher by 0.13 percentage point in comparison with the **1M** strategy. However, the difference is not statistically significant as $t = 0.28$ for two-sample t-test.

	1M	**Δ1M**	**3M**	**Δ3M**	**Low risk**	**Momentum**
Mean return	0.51 %	0.53 %	0.50 %	0.72 %	0.30 %	1.13 %
St. dev.	1.45%	1.52 %	1.35 %	1.20 %	0.44 %	4.09 %
|t|	1.62	1.59	1.69	2.75	3.17	1.27
p-value	0.12	0.13	0.11	0.01	0.00	0.22
Annualised return	6.31 %	6.50 %	6.15 %	**9.00 %**	3.70 %	**14.48 %**

Table 5.2: Returns of the long portfolios (ratings); T=21 (number of monthly returns)

Now, let us consider the return of long-only portfolios. Although these returns are overstated due to neglecting all transaction costs, it makes a good sense to compare individual performance relatively. Again the sentiment-based strategies tend to perform worse than the momentum-based one in terms of returns. Nevertheless, there is even a larger difference in the variance of sentiment- and momentum-based portfolios. Low-risk portfolios yield the lowest average return, however, standard deviation is unequivocally the lowest.

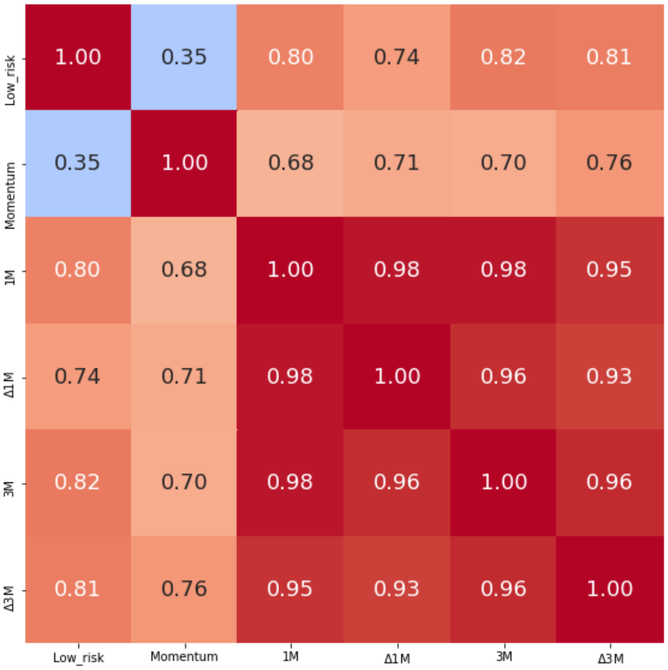


Figure 5.1: Correlation of returns - Long-only portfolios (ratings)

The **Δ3M** is again a strategy with the highest yield out of all sentiment-based approaches. More importantly, this portfolio has a considerably low value of standard deviation of its returns. Together, mean return is statistically significant at the level of 0.05.

Besides returns and their variance themselves, the correlation between the portfolios' returns can be investigated. This metric for long-only strategies is depicted by Figure **5.1**. Clearly, all the sentiment-based portfolios exhibit high pair-wise correlation (all correlation coefficients exceed 0.93). Furthermore, sentiment-base strategies seem to demonstrate higher correlation for the portfolios with the same formation period.

The pair-wise correlation between the returns of the low-risk-based portfolio and the sentiment-based ones is still pretty strong. In this case, the value ranges from 0.74 to 0.82 for **Δ1M** and **3M**, respectively. The relationship between sentiment-based portfolios and the moment-based one is a bit weaker with a correlation coefficient dropping between 0.68 and 0.76 for **1M** and **Δ3M**, respectively. Eventually, $\rho(\text{Low risk, Momentum}) = 0.35$, which proves these two strategies are quite suitable to combine to increase the level of diversification.

I also constructed four multi-factor long-only portfolios to investigate the effect of combination of two or three factors on the mean return and variance. For this purpose, the top $|\mathcal{B}_t|/2$ or $|\mathcal{B}_t|/3$ from single portfolios are picked for the multi-factor one in case of two or three factors respectively. For a reminder, $|\mathcal{B}|$ denotes the total number of bonds chosen for each one of single-factor portfolios. In this case, $|\mathcal{B}|$ is 30. The results of this analysis are displayed in Table **5.3**. In that table, **LR** and **M** are used as an abbreviations for **Low risk** and **Momentum**,

	LR+M	**LR+Δ3M**	**M+Δ3M**	**LR+M+Δ3M**	**Full**
Mean return	0.58 %	0.45 %	0.83 %	0.57 %	0.72 %
St. dev.	1.93 %	0.79 %	2.40 %	2.04 %	1.76 %
|t|	1.39	2.60	1.58	1.29	1.87
p-value	0.18	0.02	0.13	0.21	0.08
Annualised return	7.24 %	5.50 %	**10.41 %**	7.09 %	8.98 %

Table 5.3: Returns of the long multi-factor portfolios (ratings); T=21

respectively. **Full** represents the portfolio constructed with **LR+M+Δ3M** strategy and consisting of full-sized single portfolios, i.e. the portfolio consists of 90 trades.

Interestingly, even the most diversified **Full** portfolio, containing 90 bonds, performs worse than the single **Δ3M** one, consisting only of 30 bonds, considering comparable returns, but higher variance. Unfortunately, adding a **Δ3M** criterion to **LR+M** and keeping the same size of the whole portfolio leads to slightly poorer results both in terms of average monthly returns and standard deviation. Also, although **LR+Δ3M** tends to generate higher returns than the **Δ3M** portfolio, this increment is rather overshadowed by a significant rise in the variance of returns.

5.2 Comparison of Different NLP Sentiment Scoring Methods

Once BERT was fine-tuned on the training and validation data sets[1], the reviews were scored with this model and the same analysis as in previous section was conducted. With respect to the poor returns on the long-short portfolios documented in the previous Section **5.1**, results only for the long portfolios are reported for NLP sentiment scoring methods. Sections **5.2.1** and **5.2.2** provide results on the portfolios using unweighted and weighted sentiment scoring, respectively.

5.2.1 Unweighted Scoring

When sentiment is proxied by unweighted reviews instead of star ratings, one can see the results are relatively similar to the ones obtained with ratings except for a few nuances. The one difference is that the return on the **Δ3M** portfolio is not as elevated as in the previous case. On the other hand, standard deviation of returns on this portfolio is noticeably lower.

In general, however, we can conclude these findings based on unweighted reviews are more or less in alignment with the results utilising ratings for the calculation of sentiment. That, overall, means the returns on sentiment-based portfolios are higher than on the low risk-based

[1] During the fine-tuning phase, the accuracy reached on validation set was only 35.0 %.

	1M	Δ1M	3M	Δ3M	Low risk	Momentum
Mean return	0.60 %	0.55 %	0.58 %	0.66 %	0.30 %	1.13 %
St. dev.	1.29 %	1.14 %	1.69 %	1.08 %	0.44 %	4.09 %
|t|	2.13	2.19	1.57	2.80	3.17	1.27
p-value	0.05	0.04	0.13	0.01	0.00	0.22
Annualised return	7.40 %	6.75 %	7.17 %	**8.20 %**	3.70 %	**14.48 %**

Table 5.4: Returns of the long portfolios (unweighted reviews); T=21

	LR+M	LR+Δ3M	M+Δ3M	LR+M+Δ3M	Full
Mean return	0.58 %	0.39 %	0.49 %	0.44 %	0.48 %
St. dev.	1.93 %	1.10 %	1.56 %	1.06 %	1.00 %
|t|	1.39	1.63	1.45	1.90	2.19
p-value	0.18	0.12	0.17	0.07	0.04
Annualised return	7.24 %	4.81 %	**6.00 %**	5.39 %	5.19 %

Table 5.5: Returns of the long multi-factor portfolios (unweighted reviews); T=21

one, and obviously lower compared with the returns of the momentum-based portfolio. Also, variance of sentiment-based portfolio is somewhere between and rather closer to the dispersion of the low-risk portfolio. On this occasion, the variance of sentiment-based portfolios is lower than in the first experiment in three cases out of four. Lower variance also results in statistically significant returns for the **1M** and **Δ1M** portfolios at the 5% level, and for **3M** at the 1% level.

Subsequently, we can again investigate the matrix depicting the correlation among the returns of individual portfolios (see Figure **5.2**). Here, we can conclude the portfolios based on the sentiment score proxied by unweighted reviews exhibit slightly higher correlation with the low risk-based portfolio. On the contrary, the correlation with the momentum-based portfolio is marginally lower. This appears to correspond with the fact that the variance of the portfolios constructed using review-based sentiment tends to be lower than in the case of rating-based sentiment score.

Finally, we again construct multi-factor portfolio as in Section **5.1**. In this case, the results are again quite disappointing, as diversification does not bring the coveted effect. More importantly, none of multi-factor portfolios outperforms the **Δ3M**. Only the **LR+M+Δ3M** and **Full** portfolios perform a bit lower variance, nonethless, the difference is negligible as it ranges from 0.02 and 0.08 percentage points.

Additionally, only returns on the **Full** portfolio, consisting of three times more bonds than others, is statistically significant at the 5% level.

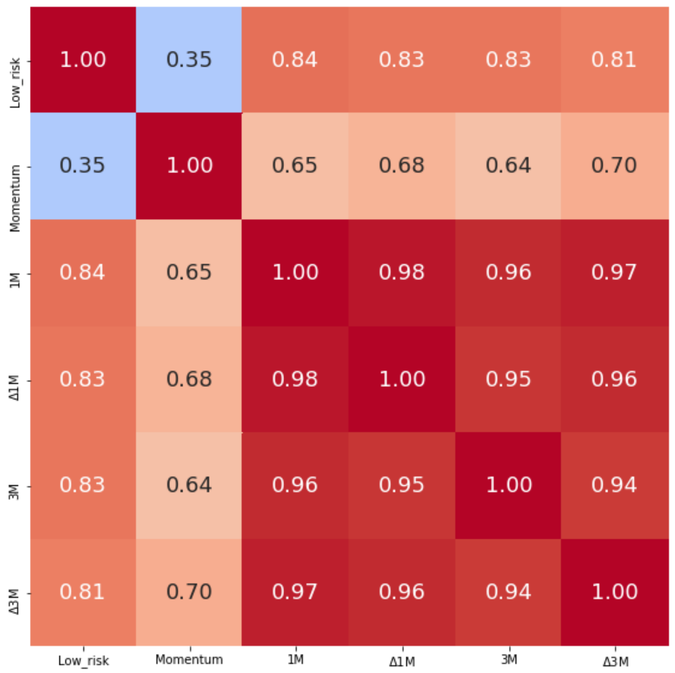


Figure 5.2: Correlation of returns - Long-only portfolios (unweighted reviews)

5.2.2 Weighted Scoring

Eventually, the same experiment with sentiment score using weighted reviews was conducted. The weighting was based on the reviews' length in words. The returns on the **1M**, **Δ1M** and **Δ3M** are on par with themselves both in terms of average return and its standard deviation. Contradictory with the previous results, the **3M** portfolio generates the highest return out of all sentiment-based portfolios. None of the portfolios generates statistically significant returns (at the 5% level). The magnitude of returns and their variance are in the range of characteristics given by the baseline portfolios.

	1M	**Δ1M**	**3M**	**Δ3M**	**Low risk**	**Momentum**
Mean return	0.47 %	0.46 %	0.64 %	0.48 %	0.30 %	1.13 %
St. dev.	1.73 %	1.43 %	1.62 %	1.61 %	0.44 %	4.09 %
|t|	1.24	1.45	1.80	1.36	3.17	1.27
p-value	0.23	0.16	0.09	0.19	0.00	0.22
Annualised return	5.81 %	5.66 %	**7.94 %**	5.86 %	3.70 %	**14.48 %**

Table 5.6: Returns of the long portfolios (weighted reviews); T=21

Considering the pair-wise correlation of returns for the last time, a reader can see the **3M** is fairly outstanding among other sentiment-based ones. This portfolio is really strongly correlated with the **low risk** portfolio, whereas it has the lowest correlation with the momentum-based one among all single-factor sentiment-based portfolios.

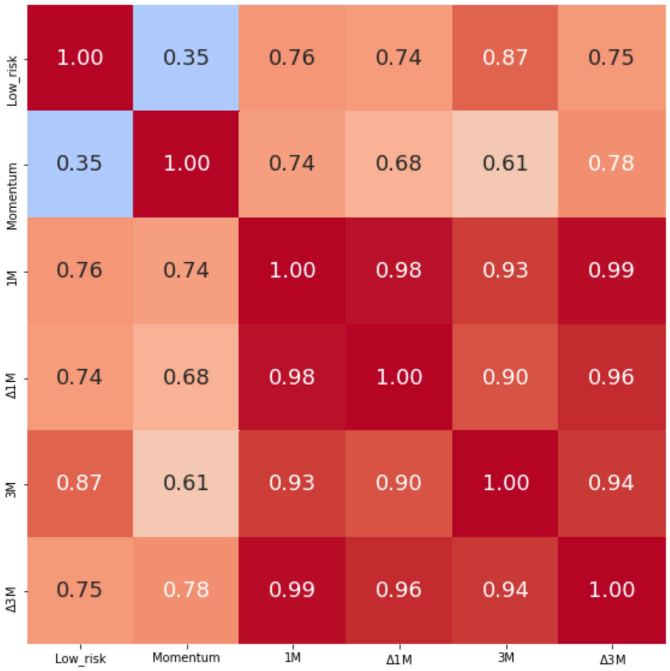


Figure 5.3: Correlation of returns - Long-only portfolios (weighted reviews)

It is noticeable to mention that utilising sentiment measured by weighted reviews leads to narrower difference in the correlation with the momentum-based and low risk-based portfolios, respectively. This is, though, quite surprising considering poorer results (in terms of returns and their significance) of the last experiment otherwise.

It is no big surprise that the results on multi-factor portfolios considering sentiment scoring are again rather poor in comparison with the single-factor portfolios. In this case, however, the deterioration in returns is even more pronounced. This is very likely a fall out of worse performance of single-factor sentiment-based portfolios.

	LR+M	**LR+Δ3M**	**M+Δ3M**	**LR+M+Δ3M**	**Full**
Mean return	0.58%	0.26 %	0.32 %	0.30 %	0.39 %
St. dev.	1.93 %	1.19 %	2.18 %	1.05 %	0.98 %
|t|	1.39	1.01	0.68	1.05	1.82
p-value	0.18	0.16	0.25	0.15	0.04
Annualised return	**7.24 %**	3.20 %	3.94 %	3.71 %	4.77 %

Table 5.7: Returns of the long multi-factor portfolios (weighted reviews); T=21

6. Discussion

In the beginning, this chapter discusses the significance and interpretation of results derived in the previous chapter. Then, the limitations of my approach altogether with potential applications are considered. Eventually, the chapter proposes recommendations for future work conducted by other researchers.

6.1 Interpretation of Results

The exploratory analysis presented in Chapter **3** (Data - Selection, Sources and Exploration) and in the Appendix shows the employee sentiment evolves over time across the markets as well as their sectors. This does, therefore, suppose to exploit this signal during the bond selection. The findings in this thesis suggest using employee sentiment proxied by information from Glassdoor may bring a valuable information for that process.

More specifically for single-factor portfolios, I found that sorting companies according to sentiment score and then picking bonds with the shortest maturity provided us with a solid increase in an average return compared with the scenario relying on the latter strategy only. This difference was the most prominent for the rating-based sentiment using monthly changes in 3-month average score. In that case, an average monthly return rose from 0.30 % to 0.72 %. Although this difference was not statistically significant at the 5% level (p-value=0.07), it suggests there can exist a meaningful benefit of incorporating the employee sentiment into the investment process. Furthermore, an average return on the **Δ3M** portfolio was highly statistically significant at the 1% level.

The scoring methods using reviews instead of star ratings generated worse results. This fall may have been caused by inaccurate predicting of positive, neutral and negative reviews by the language model. The drop in the portfolios' returns was even more obvious when the reviews were weighted with respect to their length. The latter was likely to be affected by a combination of two aspects:

- employees tend to rate lower their former employers than current ones (3.35 vs 3.80 based upon ratings),

- employees write longer reviews for former employers than current ones (34.58 vs 31.91 is an average length in words).

Therefore, in the situations when some companies receive a higher number of reviews from their past workers, their sentiment score might become skewed and not perfectly reflect the reality.

Beside the returns themselves, this thesis also considered a pair-wise correlation between the portfolios' performance. Considering the formula for calculation t-statistics for the correlation coefficient

$$t = \frac{r\sqrt{n-2}}{\sqrt{1-r^2}}, \tag{6.1}$$

where r denotes the value of correlation and n is a number of observation, the correlation between the sentiment-based and baseline portfolios' returns was found to be statistically significant at the 1% level.

I observed that the bond selection utilising the sentiment score (or its difference) noticeably elevated the correlation with the momentum-based portfolio in comparison with a simplified low risk approach. There, it is worthy to notice the correlation went up from 0.35 to somewhere around 0.7. It is not straightforward to explain such an upsurge. If we proceed from the fact that momentum strategy is based on buying winners, it may suggest itself that successful organisations are more likely to treat their employee better. The process of rising employee sentiment simultaneously with company's performance is also plausible, a verification of these hypotheses, however, would require further investigation.

Last but not least, the performance of multi-factor portfolios was scrutinised as well. The results, in that case, were quite dissatisfying as diversification did not bring a desired effect. The multi-factor utilising sentiment usually tended to underperform their single-factor counterparts both in terms of average returns and their variance. This probably stemmed from a relatively high positive correlation of sentiment-base portfolios with the baseline ones. Also, neither of results, except for the **LR+Δ3M** portfolio, was not statistically significant at the 5% level.

6.2 Limitations

In this Masters dissertation, some concessions were made with respect to the reality in finance. The results, therefore, must be considered with a bit of caution. Most importantly, I did neglect transaction costs, assumed frictionless markets and did not address market liquidity. As a consequence of these assumptions, it might be either impossible to execute all orders in practice or to achieve the reported returns as they may have been impeded by various fees in the real world.

This thesis, furthermore did not work with all outstanding bonds in the monitored time period, since these data were not retrievable with the used API. Hence it is questionable in which way the results would be affected if all the ever available data were used.

Besides, one can observe the results for the review-based sentiment score looks to be a bit worse than for the rating-based score. This analysis might have been negatively affected by a poor performance of the language model. Also, non-separating of star ratings and reviews of former and current employees for a given employer should be also mentioned among possible drawbacks of my approach. One concern regarding the latter pitfall is the fact that I cannot control when and how a given person left its employment or was ousted from a position. Some comments are, therefore, possible to be:

- irrelevant, as they were posted by people not working for a given company for a long time, or
- too bitter since some persons might have felt really angry, for example, after being dismissed.

Focusing on the employee data in more details, it should be said a small number of data points for some enterprises might be also problematic. Consequently, it could have happened the sentiment score for some companies was calculated based upon one or two ratings in a given month, which did not have to be necessarily objective. On the other hand, filtering out companies with less than, for instance, 5 or 10 reviews per month would significantly cut down the number of companies, and such an approach might be harmful as well. To illustrate this reduction, the median number of reviews per company (listed on S&P 500) in the period stretching over 2 years 222.0. It would be, therefore, necessary to drop more than a half of the firms.

Another limitation of this study is that only aggregated ratings from Glassdoor were used for my analysis. It might be insightful to study sub-scores because it is not out of the question individual components of the rating are related to the bond performance in different ways. As introduced in Chapter **3** (Data - Selection, Sources and Exploration), these constituents are: *work/life balance, culture & values, career opportunities, compensation and benefits, and senior management.*

6.3 Application

In spite of potential limitations of my work discussed above, I believe the results still provide us with promising results. They indicate there exists a relationship between the employee sentiment and the future returns on bonds of corresponding companies. I can imagine this criterion is not likely to be usable as a single factor for investing in a security of any kind. I would rather suppose the employee sentiment can be used as a complementary gauge of companies' health when evaluating the risk of an investment.

It can be also useful to build a mechanism that warns an investor when an unusual deterioration in the employee sentiment of a company occurs. For example, if that slump would be rooted in a rising dissatisfaction with senior management, it might be wise to opt out from a long buy position, as this worsening situation in that company may lead to a departure of employees who are lower in the hierarchy or so. However, a further and deeper analysis would be required to conduct to find out whether worsening employee satisfaction has eventually such fall-outs.

6.4 Future Work

There are multiple exciting directions for future research to be considered. Incorporating individual sub-scores of star ratings into the factor model is one of them coming directly to my mind. In this case, it might be worthy to investigate whether and how sorting companies with respect to five different sentiment score metrics differ. And also, what impact this eventually has on the bond selection.

I would also suggest to study whether confining sentiment calculation only on current employees has any significant effect on the experiment results. Regarding the issue of former and current employees, it might be also interesting to shed light on the varying number of posted reviews in time as well. In this place, I would propose a hypothesis whether an increasing number of reviews written by past employees is somehow correlated with a growth in employee turnover rate. This could be a valuable insight since there is evidence based on meta-analysis suggesting a negative relationship between the fluctuation of employees and companies' performance (Hancock et al., 2013).

The last idea, I would like to express, is to use a topic modelling to explore what reviewers talk about. These results can be again studied whether they have power to predict future bonds performance. I would also point out that due to a relatively simple structure of the Glassdoor reviews, this analysis might potentially be achieved with a simple rule-based algorithm that would just observe an occurrence of some words and phrases related to the work environment, work-life balance and other related topics.

7. Conclusion

This chapter highlights key findings and scientific contributions of this study, which among others include the developed scraping and storing tools (now freely available to other researchers). The dissertation is concluded by setting a direction for future research.

In this study, I focused on the utilisation of employee sentiment proxied by star ratings and reviews from Glassdoor for the factor investing in the corporate bond market. First, I found employee sentiment evolved over time and differed across companies, markets as well as market sectors. This suggested there existed a possibility to exploit this characteristic for a company selection during the portfolio construction.

For that purpose, I calculated the sentiment score for each company in a one-month and three-month period, altogether with monthly changes. Subsequently, for top decile companies bonds with the shortest maturity were picked for the portfolio. In my simplified scenario, I observed this strategy led to an increase in monthly returns from 0.30 % to 0.72 % (3.70 % and 9.00 % annually) compared with a simplified low-risk counterpart relying on the maturity selection only. Moreover, my sentiment-based portfolio exhibited a noticeably lower standard deviation of monthly returns than a momentum-based portfolio (1.20 % vs. 4.09 %).

These promising findings suggest employee sentiment can be incorporated into the portfolio construction process as a part of still more expanding socially responsible investing. I base this claim on the fact that considering this non-financial indicator into an investment process does not harm an investor's profit while focusing on companies treating their employees well.

Consequently to my results, I proposed investigating individual sub-scores, which are used for the calculation of aggregated star ratings, and topic modelling for employee reviews as the most promising direction for future research as this information may further reveal employees' opinion of their employer. To facilitate this kind of research, I provide code for interwoven scraping tools and database which were used for this thesis. The documentation can be found at my GitHub repository. All the essential components of this pipeline can be easily run from command line enabling to run scraping on UCL clusters without the necessary supervision of a researcher.

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Appendix

Appendix A - Descriptive Statistics - Ratings

1. Number of ratings/reviews across market sectors (for stock market indices)

S&P 500

Market sector	Mean	Std	10^{th}	Q1	Median	Q3	90^{th}
Basic Materials	139.5	218.69	38.1	48.0	64.0	100.5	256.2
Communications	897.8	1058.33	37.3	145.0	413.5	1275.3	2289.3
Consumer Cyclical	1391.4	3801.78	63.4	119.0	232.0	1139.0	2358.2
Consumer Defensive	945.08	2139.30	70.0	119.8	278.5	590.5	1558.5
Energy	215.96	285.08	26.0	50.0	92.0	241.0	644.6
Financial Services	655.43	938.28	60.9	160	328.5	610.5	1613.2
Healthcare	459.44	610.05	77.0	127	241.0	532.0	905.0
Industrials	493.25	653.78	61.0	117	268.0	646.0	1022.6
Real Estate	150.26	238.89	12.2	31.5	93.0	163.0	233.6
Technology	1198.45	2361.90	71.2	140.8	352.5	1014.8	3234.2
Utilities	68.72	37.15	26.4	34.0	71.0	90.0	110.0

FTSE 100

Market ector	Mean	Std	10^{th}	Q1	Median	Q3	90^{th}
Basic Materials	97.78	88.99	18.0	39.0	62.0	126.0	239.8
Communications	375.40	685.92	54.0	71.5	88.0	230.8	850.9
Consumer Cyclical	251.60	257.29	61.8	71.5	219.0	250.5	521.4
Consumer Defensive	726.36	1118.22	37.0	76.5	402.0	533.5	2042.0
Energy	722.00	830.14	252.4	428.5	722.0	1015.5	1191.6
Financial Services	633.41	1034.60	57.8	95.0	134.0	849.0	1958.4
Healthcare	566.00	538.44	112.1	187.3	471.5	850.3	1095.5
Industrials	188.30	153.49	16.5	41.0	194.0	301.3	338.1
Real Estate	15.00	4.24	12.6	13.5	15.0	16.5	17.4
Technology	41.50	2.12	40.3	40.8	41.5	42.3	42.7
Utilities	156.75	86.21	75.7	93.3	163.5	227.0	232.4

EURO STOXX 50

Market sector	Mean	Std	10th	Q1	Median	Q3	90th
Basic Materials	101.75	69.11	42.4	55.0	91.5	138.3	169.3
Communications	244.67	234.54	83.8	112.0	159.0	334.5	439.8
Consumer Cyclical	254.50	231.45	127.5	147.3	150.0	230.0	486.0
Consumer Defensive	529.00	427.76	120.6	237.0	567.0	639.0	951.0
Energy	165.50	116.67	99.5	124.3	165.5	206.8	231.5
Financial Services	315.78	309.61	53.0	73.0	225.0	498.0	640.6
Healthcare	400.25	300.88	104.7	221.3	458.0	637.0	649.6
Industrials	597.86	737.02	51.4	123.0	280.0	865.5	1592.2
Real Estate	66.00	N/A	66.0	66.0	66.0	66.0	66.0
Technology	2391.33	2115.38	633.6	1489.5	2916.0	3555.5	3939.2
Utilities	153.67	100.02	70.4	114.5	188.0	210.0	223.2

2. Ratings across market sectors (for stock market indices)

S&P 500

Market sector	Mean	Std	Q1	Median	Q3
Basic Materials	3.57	1.21	3.0	4.0	4.0
Communications	3.61	1.29	3.0	4.0	5.0
Consumer Cyclical	3.63	1.22	3.0	4.0	5.0
Consumer Defensive	3.34	1.27	3.0	3.0	4.0
Energy	3.58	1.18	3.0	4.0	4.0
Financial Services	3.58	1.22	3.0	4.0	5.0
Healthcare	3.44	1.31	3.0	4.0	5.0
Industrials	3.55	1.27	3.0	4.0	5.0
Real Estate	3.68	1.36	3.0	4.0	5.0
Technology	3.73	1.16	3.0	4.0	5.0
Utilities	3.58	1.32	3.0	4.0	5.0

FTSE 100

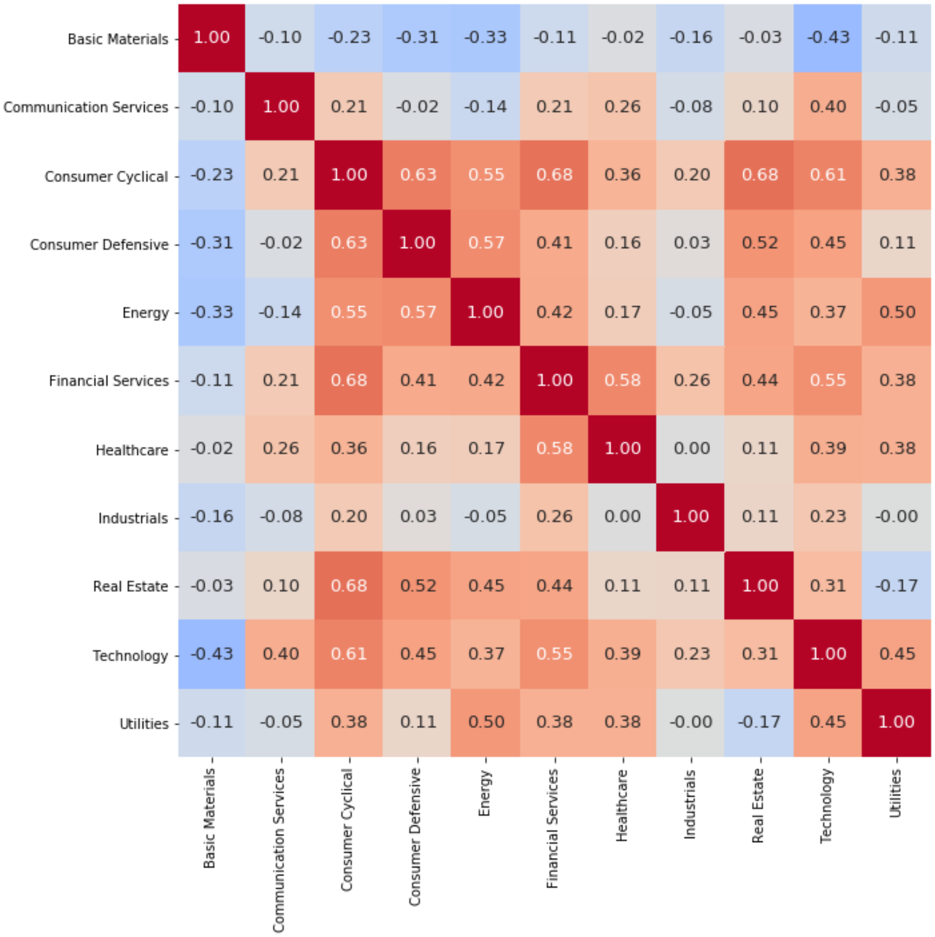
Market sector	Mean	Std	Q1	Median	Q3
Basic Materials	3.61	1.22	3.0	4.0	5.0
Communications	3.58	1.21	3.0	4.0	5.0
Consumer Cyclical	3.44	1.34	3.0	4.0	5.0
Consumer Defensive	3.55	1.18	3.0	4.0	4.0
Energy	3.93	1.12	3.0	4.0	5.0
Financial Services	3.65	1.12	3.0	4.0	4.0
Healthcare	3.76	1.16	3.0	4.0	5.0
Industrials	3.63	1.37	3.0	4.0	5.0
Real Estate	3.93	1.23	3.0	4.0	5.0
Technology	3.58	1.23	3.0	4.0	4.0
Utilities	3.48	1.31	3.0	4.0	5.0

EURO STOXX 50

Market sector	Mean	Std	Q1	Median	Q3
Basic Materials	3.42	1.34	3.0	4.0	5.0
Communications	3.81	1.06	3.0	4.0	5.0
Consumer Cyclical	3.80	1.13	3.0	4.0	5.0
Consumer Defensive	3.71	1.22	3.0	4.0	5.0
Energy	3.66	1.21	3.0	4.0	5.0
Financial Services	3.51	1.20	3.0	4.0	4.0
Healthcare	3.69	1.16	3.0	4.0	5.0
Industrials	3.90	1.10	3.0	4.0	5.0
Real Estate	3.23	1.45	2.0	4.0	4.0
Technology	4.29	0.98	4.0	5.0	5.0
Utilities	3.49	1.25	3.0	4.0	4.0

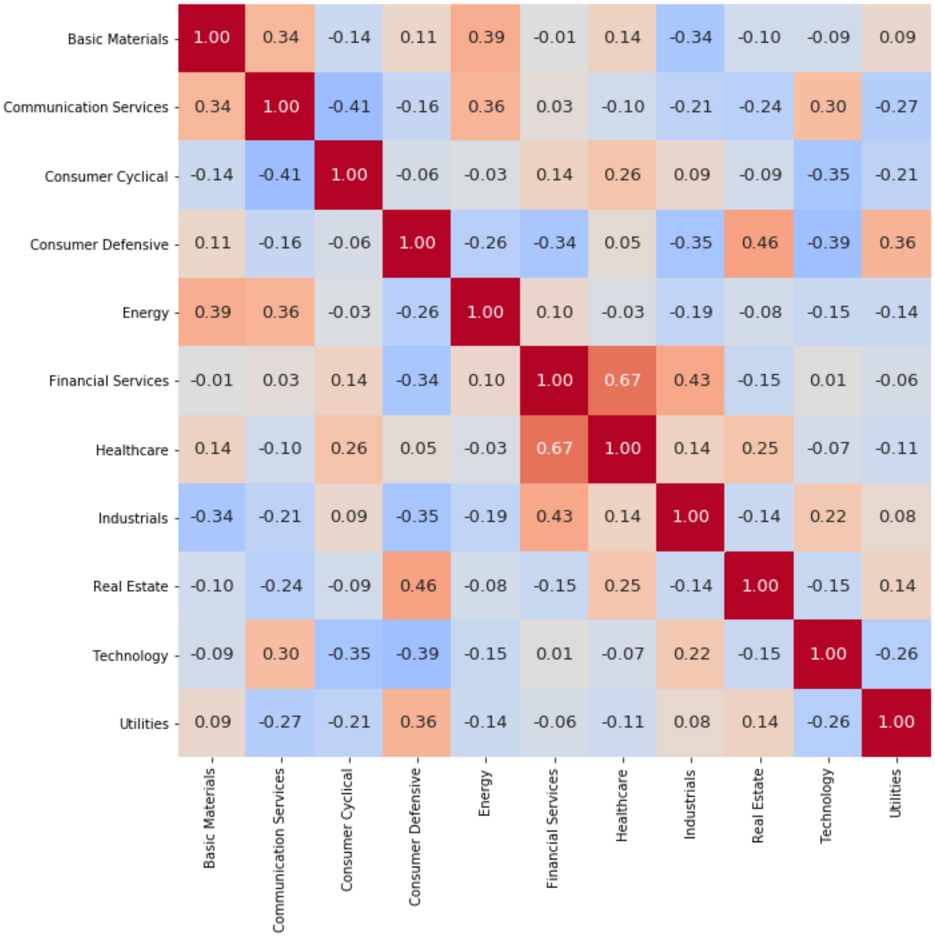
4. Correlation of monthly changes in ratings across market sectors (for stock market indices)

S&P 500



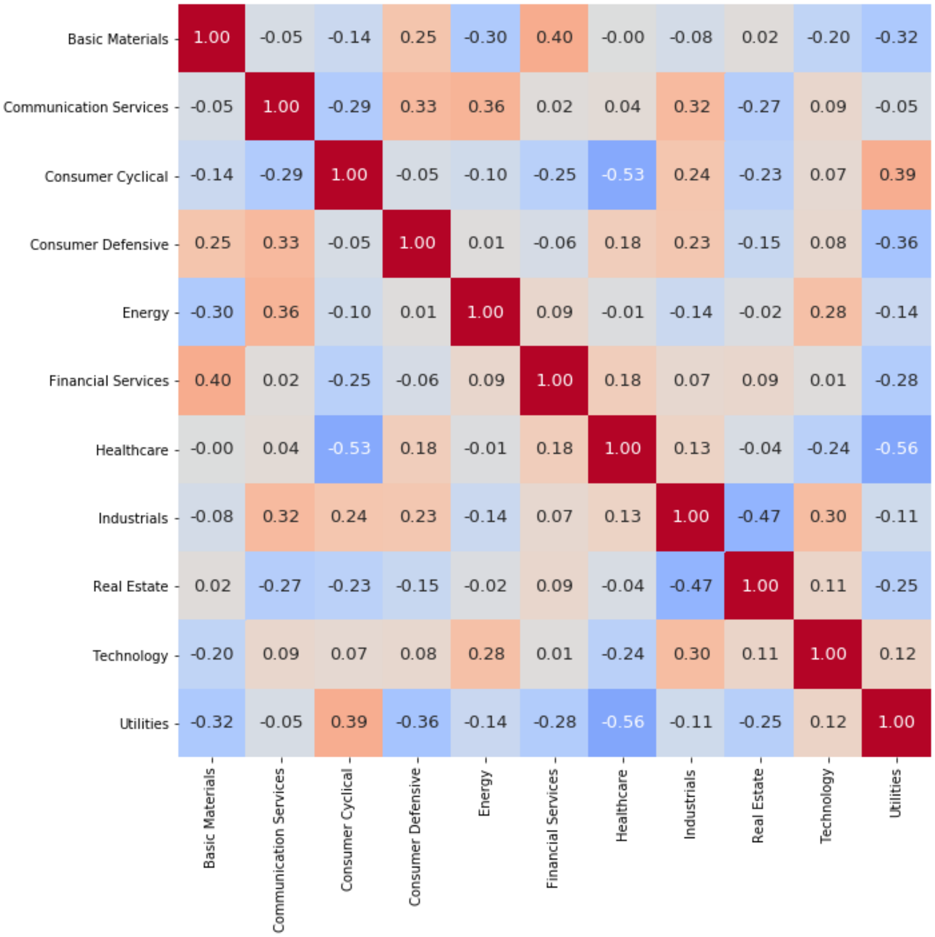
	Basic Materials	Communication Services	Consumer Cyclical	Consumer Defensive	Energy	Financial Services	Healthcare	Industrials	Real Estate	Technology	Utilities
Basic Materials	1.00	-0.10	-0.23	-0.31	-0.33	-0.11	-0.02	-0.16	-0.03	-0.43	-0.11
Communication Services	-0.10	1.00	0.21	-0.02	-0.14	0.21	0.26	-0.08	0.10	0.40	-0.05
Consumer Cyclical	-0.23	0.21	1.00	0.63	0.55	0.68	0.36	0.20	0.68	0.61	0.38
Consumer Defensive	-0.31	-0.02	0.63	1.00	0.57	0.41	0.16	0.03	0.52	0.45	0.11
Energy	-0.33	-0.14	0.55	0.57	1.00	0.42	0.17	-0.05	0.45	0.37	0.50
Financial Services	-0.11	0.21	0.68	0.41	0.42	1.00	0.58	0.26	0.44	0.55	0.38
Healthcare	-0.02	0.26	0.36	0.16	0.17	0.58	1.00	0.00	0.11	0.39	0.38
Industrials	-0.16	-0.08	0.20	0.03	-0.05	0.26	0.00	1.00	0.11	0.23	-0.00
Real Estate	-0.03	0.10	0.68	0.52	0.45	0.44	0.11	0.11	1.00	0.31	-0.17
Technology	-0.43	0.40	0.61	0.45	0.37	0.55	0.39	0.23	0.31	1.00	0.45
Utilities	-0.11	-0.05	0.38	0.11	0.50	0.38	0.38	-0.00	-0.17	0.45	1.00

FTSE 100



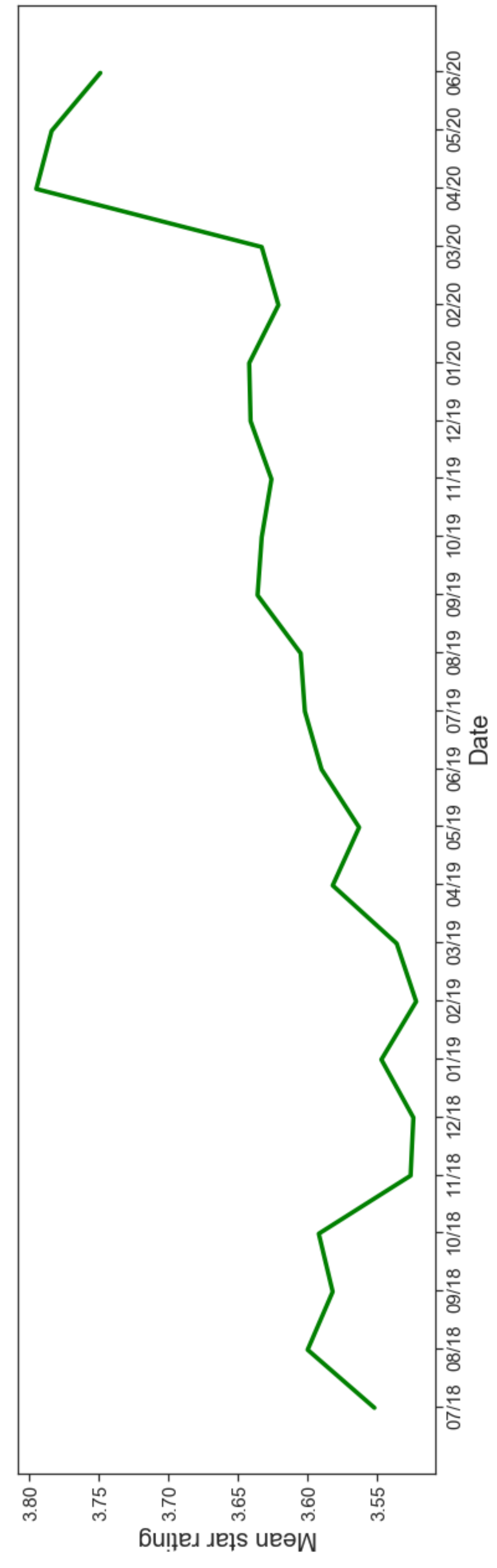
	Basic Materials	Communication Services	Consumer Cyclical	Consumer Defensive	Energy	Financial Services	Healthcare	Industrials	Real Estate	Technology	Utilities
Basic Materials	1.00	0.34	-0.14	0.11	0.39	-0.01	0.14	-0.34	-0.10	-0.09	0.09
Communication Services	0.34	1.00	-0.41	-0.16	0.36	0.03	-0.10	-0.21	-0.24	0.30	-0.27
Consumer Cyclical	-0.14	-0.41	1.00	-0.06	-0.03	0.14	0.26	0.09	-0.09	-0.35	-0.21
Consumer Defensive	0.11	-0.16	-0.06	1.00	-0.26	-0.34	0.05	-0.35	0.46	-0.39	0.36
Energy	0.39	0.36	-0.03	-0.26	1.00	0.10	-0.03	-0.19	-0.08	-0.15	-0.14
Financial Services	-0.01	0.03	0.14	-0.34	0.10	1.00	0.67	0.43	-0.15	0.01	-0.06
Healthcare	0.14	-0.10	0.26	0.05	-0.03	0.67	1.00	0.14	0.25	-0.07	-0.11
Industrials	-0.34	-0.21	0.09	-0.35	-0.19	0.43	0.14	1.00	-0.14	0.22	0.08
Real Estate	-0.10	-0.24	-0.09	0.46	-0.08	-0.15	0.25	-0.14	1.00	-0.15	0.14
Technology	-0.09	0.30	-0.35	-0.39	-0.15	0.01	-0.07	0.22	-0.15	1.00	-0.26
Utilities	0.09	-0.27	-0.21	0.36	-0.14	-0.06	-0.11	0.08	0.14	-0.26	1.00

EURO STOXX 50



	Basic Materials	Communication Services	Consumer Cyclical	Consumer Defensive	Energy	Financial Services	Healthcare	Industrials	Real Estate	Technology	Utilities
Basic Materials	1.00	-0.05	-0.14	0.25	-0.30	0.40	-0.00	-0.08	0.02	-0.20	-0.32
Communication Services	-0.05	1.00	-0.29	0.33	0.36	0.02	0.04	0.32	-0.27	0.09	-0.05
Consumer Cyclical	-0.14	-0.29	1.00	-0.05	-0.10	-0.25	-0.53	0.24	-0.23	0.07	0.39
Consumer Defensive	0.25	0.33	-0.05	1.00	0.01	-0.06	0.18	0.23	-0.15	0.08	-0.36
Energy	-0.30	0.36	-0.10	0.01	1.00	0.09	-0.01	-0.14	-0.02	0.28	-0.14
Financial Services	0.40	0.02	-0.25	-0.06	0.09	1.00	0.18	0.07	0.09	0.01	-0.28
Healthcare	-0.00	0.04	-0.53	0.18	-0.01	0.18	1.00	0.13	-0.04	-0.24	-0.56
Industrials	-0.08	0.32	0.24	0.23	-0.14	0.07	0.13	1.00	-0.47	0.30	-0.11
Real Estate	0.02	-0.27	-0.23	-0.15	-0.02	0.09	-0.04	-0.47	1.00	0.11	-0.25
Technology	-0.20	0.09	0.07	0.08	0.28	0.01	-0.24	0.30	0.11	1.00	0.12
Utilities	-0.32	-0.05	0.39	-0.36	-0.14	-0.28	-0.56	-0.11	-0.25	0.12	1.00

5. Average star rating over time



Appendix B - Descriptive Statistics - Reviews

1. Length of reviews (in words) across stock market sectors

Market Sector	Mean	Std	10th	Q1	Median	Q3	90th
Masic Materials	34.60	50.25	11	13	19	35	70
Communications	35.13	55.93	11	13	18	34	72
Consumer Cyclical	32.32	48.93	11	13	18	32	64
Consumer Defensive	30.93	46.81	11	13	17	30	60
Energy	30.27	47.00	11	13	17	29	58
Financial Services	31.43	47.69	11	13	17	30	61
Healthcare	34.83	50.32	11	13	18	35	73
Industrials	35.88	56.41	11	13	19	35	74
Real Estate	46.84	66.06	11	14	23	52	104
Technology	31.99	50.60	11	13	17	31	63
Utilities	38.21	59.17	11	13	20	40	79

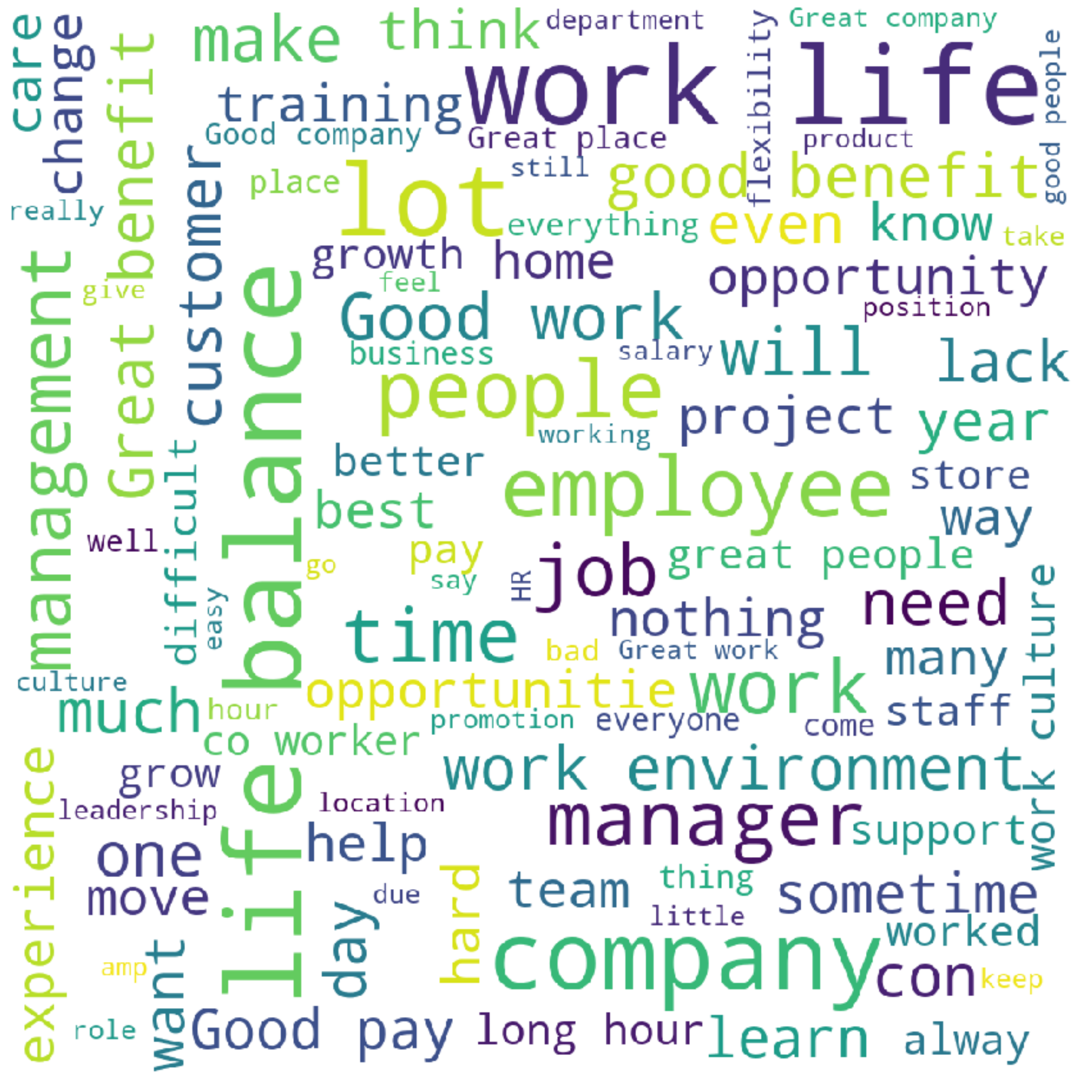
2. Length of reviews (in words) across stock market indices

Stock market	Mean	Std	10th	Q1	Median	Q3	90th
S&P 500	33.37	51.74	11	13	18	32	67
FTSE 100	29.70	42.88	11	12	17	29	58
EURO STOXX 50	29.66	40.92	11	13	17	30	58

3. Length of reviews across employee categories

Employee	Total reviews	Mean	Std	10th	Q1	Median	Q3	90th
Full-time	316,117	33.79	52.14	11	13	18	33	68
Part-time	58,240	28.76	41.83	11	12	17	28	54
Not specified	18,043	29.48	46.00	11	12	16	28	58
Current	220,135	31.91	46.63	11	13	18	31	64
Former	154,224	34.58	55.98	11	13	18	33	69
Not specified	18,041	29.48	46.00	11	12	16	28	58
Total	392,408	32.85	50.51	11	13	18	32	66

4. Wordcloud


care
change
benefit
make
think
department
flexibility
Great company
work life
good people
training
Good company
Great place
product
still
really
place
lot
good
benefit
Great benefit
customer
everything
even
know
take
management
balance
growth
home
feel
opportunity
give
position
Good work
business
salary
will
lack
people
project
year
working
better
employee
store
difficult
best
way
well
pay
great people
go
say
HR
job
easy
need
time
nothing
culture
bad
Great work
many
culture
opportunitie
work
much
hour
promotion
everyone
come
staff
co worker
grow
work environment
experience
leadership
location
life
manager
support
work
one
help
thing
move
team
sometime
due
little
hard
day
worked
amp
want
company
con
keep
role
Good pay
long hour
learn
alway

Appendix C - Table scheme

```python
from django.db import models
# set max_lengths for texts of different lengths
short_text, mid_text, long_text = 25, 100, 500

class Company(models.Model):
    CompanyID = models.IntegerField(null=True)
    Company = models.CharField(max_length=mid_text, blank=True, unique=True)
    Symbol = models.CharField(max_length=short_text, blank=True)
    ListedOn = models.CharField(max_length=short_text, blank=True)
    Sector = models.CharField(max_length=mid_text, blank=True)
    Industry = models.CharField(max_length=mid_text, blank=True)
    Country = models.CharField(max_length=mid_text, blank=True)
    NoEmployees = models.IntegerField(null=True)
    Revenue = models.FloatField(null=True)
    Timestamp = models.TimeField(null=True)

    def __str__(self):
        return self.Company


class Review(models.Model):
    Company = models.ForeignKey(Company, on_delete=models.CASCADE)
    ReviewTitle = models.CharField(max_length=long_text, blank=True)
    Year = models.IntegerField(null=True)
    Month = models.IntegerField(null=True)
    Day = models.IntegerField(null=True)
    Rating = models.FloatField(null=True)
    JobTitle = models.CharField(max_length=long_text, blank=True)
    EmployeeRelationship = models.CharField(max_length=mid_text, blank=True)
    Location = models.CharField(max_length=mid_text, blank=True)
    Recommendation = models.CharField(max_length=short_text, blank=True)
    Outlook = models.CharField(max_length=short_text, blank=True)
    OpinionOfCEO = models.CharField(max_length=short_text, blank=True)
    Contract = models.CharField(max_length=mid_text, blank=True)
    ContractPeriod = models.CharField(max_length=mid_text, blank=True)
    Pros = models.CharField(max_length=long_text, blank=True)
    Cons = models.CharField(max_length=long_text, blank=True)
    AdviceToManagement = models.CharField(max_length=long_text, blank=True)
    Timestamp = models.TimeField(null=True)

    def __str__(self):
        return self.ReviewTitle
```