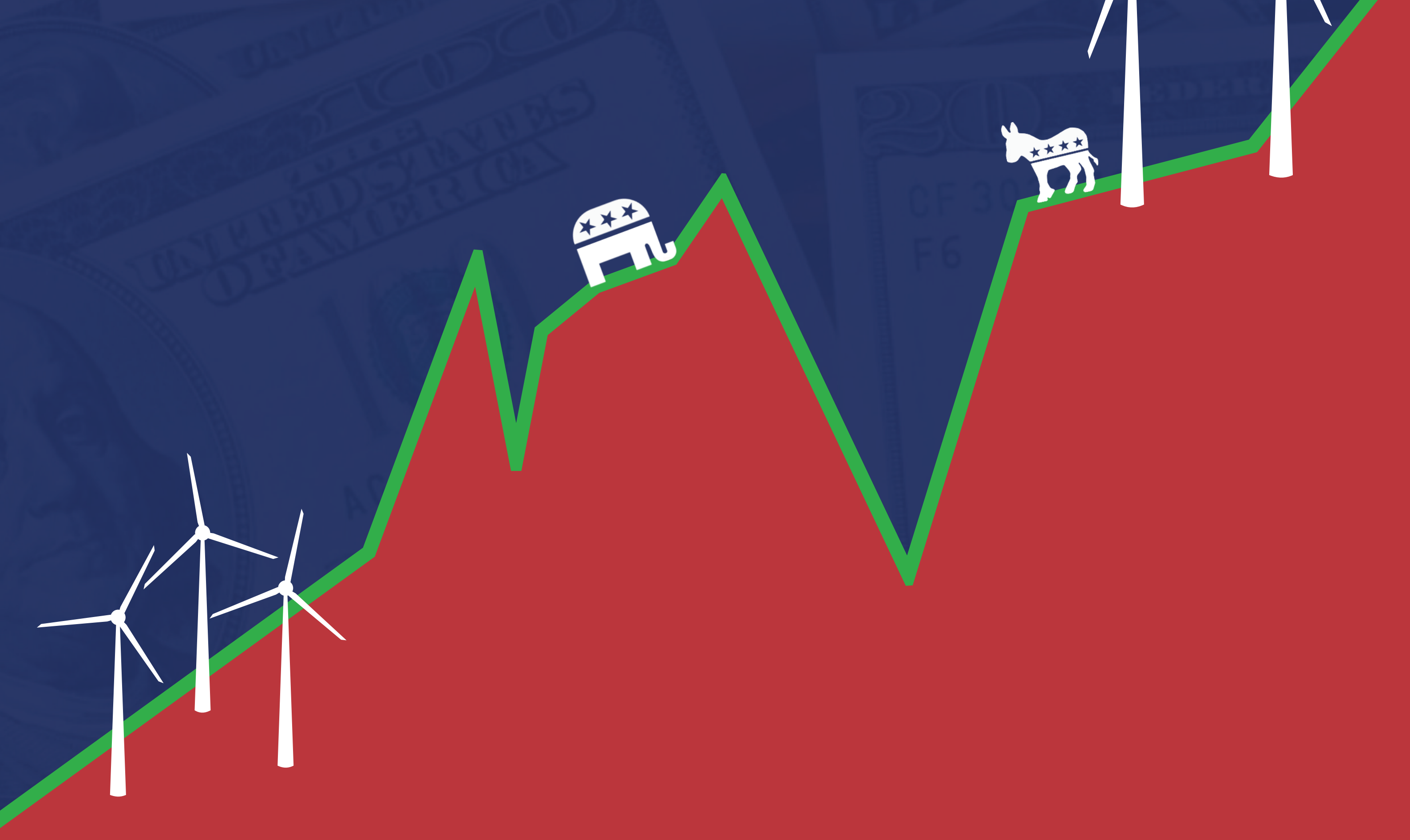
Is it time for investors to wake up?

A study on the relationship between social and financial performance



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Abstract

This thesis contributes to both investigating the link between social performance and financial performance and to how corporations' political views affect this relationship. Inspired by the article "Money where their mouths are" (The Economist, 2019), we construct a wokeness index based on companies' Environmental Social and Governance (ESG) ratings, ESG Controversies score, and corporate political donations. The ESG and ESG Controversies data is from Refinitiv and the data for political donations is provided by the Center of Responsive Politics. We focus our analysis on the U.S. market, specifically the S&P 500. We collect the data for our wokeness index from 2005-2018. We use stock returns as a proxy for financial performance and collect the stock returns for the period 2006-2019 from Datastream.

Previous literature suggests that ESG ratings have a positive influence on financial performance. However, less evidence exists on how the ESG Controversies score and the corporate political donations influence the financial performance of firms.

The econometrical framework applies a high and low portfolio approach using the Fama and French (1992) 3-factor, the Carhart (1997) 4-factor, and the Fama and French (2015) 5-factor model. Our results suggest that the relationship between our wokeness index and financial performance is U-shaped, indicating that investors benefit most from investing in both the wokest and the least woke companies. However, the results lack statistical significance.

Keywords: ESG, Corporate social performance, Financial performance, Corporate political donations

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Contents

1 Introduction

During the past decades the focus on sustainability has increased steadily. This has led to several political initiatives. In 1995 the Kyoto Protocol, which legally binds the parties to emission reduction targets, was signed by 192 nations. In 2015 all nations in the UN gathered in Paris to discuss the human impact on the environment. 195 nations agreed to combat climate change and initiate actions and investments towards a low-carbon and a more sustainable future.

Politicians are not the only ones taking action. One of the most important trends during the past decade has been the increased desire to invest in socially responsible companies. Through time many different definitions of a company's social performance have emerged. Ethical investment has always been around and is a practice where the investor excludes companies according to ethical, religious, or moral beliefs. Social Responsible Investment (SRI) emerged from ethical investing and is an approach that allows a level of trade-off between corporate social and financial performance when investing (Fulton, Kahn, & Sharples, 2012). SRI mainly uses negative screening[1], however positive screening[2] has been incorporated later. Later the demand for a more concrete definition of SRI arose, which led to the development of the ESG framework. The ESG framework includes the following factors; Environment, Social, and Corporate Governance. One of the indicators considered in the ESG framework is Corporate Social Responsibility (CSR). CSR has evolved alongside SRI and later ESG. Differently from the previously mentioned terms, CSR is employed from a business perspective rather than an investor perspective. (Fulton et al., 2012)

In 2005 the United Nations' general secretary invited some of the world's largest institutional investors to a meeting with the aim to develop the Principles for Responsible Investing (PRI), which resulted in six investment principles. The six principles "offer a menu of possible actions for incorporating ESG issues into investment practice" (PRI, 2020). The PRI suggest that investors add a third dimension of real-world impact to the traditional decision framework of risk and return. The PRI argues that ignoring ESG factors when investing is to ignore risk and opportunities that have a

[1] Negative screening: excludes companies or sectors from the investment universe based on criteria such as policies, actions, products, or services (Fulton et al., 2012).

[2] Positive screening: includes companies or sectors from the investment universe based on criteria such as policies, actions, products, or services (Fulton et al., 2012).

substantial effect on returns (PRI, 2019). Being the world's largest proponent for responsible investing the PRI has ensured that the total assets under management following the six principles, have grown from 6.5 trillion USD in 2006 to more than 85 trillion USD in 2019 (PRI, 2020). With more and more investors joining the PRI many started wondering if the returns of sustainable investing would yield abnormal returns. Most researchers, such as Lee, Faff, and Rekker (2012), Halbritter and Dorfleitner (2015), and Auer and Schuhmacher (2016), find a positive or non-negative relationship between the ESG factors and financial performance.

The frameworks for responsible investing and emission reductions have all been initiated by political institutions. As more companies strive to comply with the frameworks, private investors have also started to focus on sustainability. However, not everyone agrees on the sustainability agenda, and it has divided the political landscape around the world. Recent events suggest that the political beliefs in the United States have become more partitioned. On June 1st, 2017 President Donald Trump announced that the United States will withdraw from the Paris Agreement as he believes it will undermine the United States economy (BBC News, 2017). It appears that the values of responsible investing are more closely aligned with the Democratic party as they have incorporated many social responsibility matters into their policies (Rubin, 2008). The Democrats incorporate the sustainability factors into their strategy as they believe climate change to be one of the biggest threats to the economy and security of the country (Democratic Party Platform, 2020). This division in beliefs is also apparent in corporate U.S.. An article "Money where their mouths are" in The Economist (2019) finds a trend that "woke" companies are more likely to donate to the Democratic party. The article investigates the correlation between the percentage-wise donation to the Democrats and a "wokeness" index set up to capture how socially liberal companies are. The index includes the companies CSR score, what political initiatives the companies support, and the companies' employees' political beliefs (The Economist, 2019). They find that the technology industry is the "wokest" and the energy, chemicals, and others are the least "woke" industries.

In this thesis, "wokeness" is defined as a combination of ESG performance, the amount of controversies and the percentage-wise political donations to the Democratic Party. We conduct empirical tests to see whether the wokeness of a company is related to its financial performance. We believe that a relationship between wokeness and financial performance exists for several reasons. Firstly, there is evidence that there is a positive or non-negative relationship between ESG scores and financial performance (Fulton et al., 2012). Secondly, research has shown that there is a positive correlation between a company's social performance and political beliefs, meaning socially liberal companies tend to put more attention towards social performance compared to their more conservative peers (Di Giuli & Kostovetsky, 2014). We measure the wokeness of a company through ESG scores, ESG controversies scores, and the political donations made by companies. As we do not want to rely on only one indicator for social performance we include the ESG controversies score to correct for actions that dispute the ESG score. If companies with high ESG scores have a lot of controversies, do they really care about social performance or are they just greenwashing to seem more woke than they are?

Our data consists of ESG and ESG Controversies scores from Refinitiv. The datasets are collected from 2004 to 2018 and include the scores for S&P 500 companies. We collect the stock returns for the corresponding companies from Thomson Reuters Datastream, as we use stock returns as a proxy for financial performance. The political data is provided by the Center for Responsive Politics and consists of all political donations made by companies in the election cycles from 2006 to 2018.

We construct a wokeness index inspired by the article "Money where their mouths are" (The Economist, 2019). We use the wokeness index to construct wokeness portfolios, which are used to test if there is a relationship between social and financial performance. The wokeness portfolios are constructed based on the out- and underperformers of the index. This approach is inspired by the ESG portfolio method that generally constructs high and low portfolios based on ESG out- and underperformers, respectively (Halbritter & Dorfleitner, 2015). We rely on the Fama and French (1993) 3-factor model, the Carhart (1997) 4-factor model, and the Fama and French (2015) 5-factor model for estimating abnormal returns of our wokeness portfolios. This empirical framework is inspired by existing research on ESG and financial performance, for example, Halbritter and Dorfleitner (2015), and Lee, Faff and Rekker (2012)

Our thesis is mainly related to two strands of literature. The first strand consists of research that investigates the relationship between social performance indicators, such as ESG and CSR, and financial performance. The second strand consists of research on the relationship between corporate political donations and financial performance.

This thesis contributes to the existing empirical research on how a company's social performance affects its financial performance. In contrast to other studies we construct a unique social performance indictor that includes political donations. Our results suggest that there are differences in the financial performance of the high, low, and neutral wokeness portfolios.

1.1 Outline

The remainder of this thesis is structured as follows: section 2 creates an overview of the existing research on the three components used to define wokeness. The hypothesis that this thesis seek to test are developed and presented in section 3. Section 4 consists of two main parts; the data and method used to construct the wokeness index and the econometric framework applied. In section 5 the results of our analysis are presented. The results are interpreted in section 6. Finally, in section 7 the conclusion of the thesis is presented along with suggestions for further research.

2 Previous literature

In this section, we provide an overview of the previous literature concerning the link between a company's financial return and social performance measured in terms of CSR and ESG criteria. In addition, we provide an overview of the relationship between political donations and financial performance. Finally, we describe the current findings regarding the link between corporate social performance, financial performance, and political donations. However, the existing literature concerning this topic is very limited.

2.1 Corporate Social performance and corporate financial performance

2.1.1 CSR and corporate financial performance

In 1970 Milton Friedman famously stated: "there is one and only one social responsibility of business—to use its resources and engage in activities designed to increase its profits, so long as it stays within the rules of the game." (Friedman, 1970). However, business has changed a lot since then and Freeman (1984) argued that a firm should create value for all stakeholders, not just the shareholders. Nowadays, nearly all companies invest in CSR.

As sustainable investing has been growing for the past decade most companies seem to follow the Stakeholder Theory initiated by Freeman (1984). The increase in focus on social responsibility is linked to an increase in potential profits (Guay, Doh, & Sinclair, 2004). Prior to SRI and ESG, CSR was the precursor to involve companies in the debate of responsible business practices. CSR is a way for companies to self-regulate based on sustainable practices (Garriga & Melé, 2004). CSR has moved from being firm-specific to industry-specific with the guidelines gaining a global tone. In many instances, CSR is now mandatory at regional, national, and transnational levels. Nowadays CSR is one of the building blocks of the ESG concept, solving environmental and social issues through corporate governance (Garriga & Mele, 2004).

Over the years there have been many studies that investigate the relationship between CSR and corporate financial performance (CFP). Despite the high number of studies, the direct impact of CSR on the financial performance of a firm has remained unclear (positive, negative, or neutral) (Ali, Danish, & Asrar-ul-Haq, 2020). According to McWilliams and Siegel (2000), the empirical studies of the relationship between CSR and financial performance can be divided into two main types. The first type uses the event study methodology to assess short-run financial impact in the form of abnormal returns when firms engage in socially responsible or irresponsible acts. The second type examines the nature of the relationship between CSR and measures of long term firm performance, using accounting (return on assets, return on equity, and firm value) or market-based measures (stock price, fund returns, Tobin's Q) of profitability. The result of both types of experiments are equally mixed (McWilliams & Siegel, 2000).

Some of the older and widely cited studies include those of Ullmann (1985); McGuire, Sundgren, and Schneeweis (1988); Preston and O'Bannon (1997); Jones and Wicks (1999); McWilliams and Siegel (2000); and Orlitzky, Schmidt, and Rynes (2003). The results of these studies were not conclusive. There is a slight overweight of studies that find a positive relationship between CSR and CFP (Marom, 2006). This claim is supported by the meta-analysis of Orlinzky et al. (2003), where they review 52 previous studies. The results reveal that across studies from the previous 30 years CSP is positively correlated with CFP and that the relationship tends to be bidirectional and simultaneous. Orlinzky et al. (2003) further state that a firm's reputation seems to be an important factor in the relationship between CSR and CFP while stakeholder mismatching, sampling error, and measurement error can explain 15-100% of the cross-study variation in various subsets of CSP-CFP correlations. According to McWilliams and Siegel (2000), much of the older studies in the field suffer from important empirical and theoretical limitations making the results biased.

More recent research on the CSR-CFP relationship follows the same trend as the older research, as the results are not conclusive. However, the results tend to show a positive relationship between CFP and CSR more frequently than a negative one (Fulton et al., 2012).

Studies that suggest a *positive* relationship between CSR and CFP include those of Cavaco and Crifo (2014), Busch and Friede (2018), Barnett and Salomon (2012), and Wu (2006). Cavaco and Crifo (2014) focused their study on the interaction between different dimensions of CSR that affect the relationship between CSR and financial performance. They investigate this relationship by using a panel sample of 1094 observations which translates into 300 companies per year from 15 countries during 2002-2007. The results indicate that responsible behavior towards employees, customers, and suppliers has a positive effect on financial performance. The second-order meta-analysis of Busch and Friede (2018) indicates a significant positive bilateral relationship between corporate social and environmental performance and CFP which stays positive regardless of whether firms focus on ecological or social aspects. The data sample consisted of 25 previous meta-analyses which yielded a sample size of one million observations. Barnett and Salomon (2012) researched the shape of the corporate social performance and CFP relationship. They find that the relationship is U-shaped meaning that firms with low corporate social performance have higher CFP than firms with moderate corporate social performance. However, companies with a high corporate social performance report the highest CFP. Companies that perform well in terms of CSR improves stakeholder relations which improves the company's ability to transform social investment into financial returns. The relationship is not linear due to the fact that investing in CSR comes with costs but after a tipping point, the benefits of CSR increase at a higher rate than the costs which creates the U-shape of the relationship Barnett and Salomon (2012). Wu (2006) investigated the CSR-CFP relationship and how the size of the firm affects the relationship between those. He found that firm size does not affect either CSR or CFP but that the cost of CSR is low and firms may benefit financially from socially responsible actions.

Other studies, such as those of Van de Velde, Vermeir, and Corten (2005) and McWilliams and Siegel (2000), find a *neutral* or insignificant relationship between CSR and CFP. Van de Velde et al. (2005) use sustainability ratings from Vigeo and apply a Fama and French regression to determine the performance of the high and low rated firms. The results indicate that highly rated portfolios performed better than low-rated portfolios. However, Van de Velde et al. (2005) argue that the results are most likely due to the short horizon of the experiment and therefore not significant. McWilliams and Siegel (2000) argue that studies estimating the effect of CSR by regressing firm performance on corporate social performance and other control variables are misspecified because they do not control for investment in research and development (R&D). R&D has been shown to be an important determinant of firm performance. The exclusion of R&D results in upwardly biased estimates of the financial impact of CSR. When controlling for investments in R&D, CSR has a neutral impact on financial performance.

There is less literature on the *negative* relationship between CSR and CFP. Brammer, Brooks, and Pavelin (2006) investigated the relationship between CSR and CFP using stock returns in the UK and a set of disaggregated social performance indicators for environment, employment, and community activities. The scores on social performance indicators are negatively related to stock returns and in addition, considerable abnormal returns are available from holding a portfolio of the least desirable stocks.

Finally, a literature review conducted by Van Beurden and Gössling (2008) evaluated studies that empirically tested the relationship between CSR and CFP. The results reveal that 68% of the included studies found a positive relationship between CSP and CFP while 26% show no significant relationship between CSP and CFP. Only two studies or 6% show a negative effect between CSP and CFP.

The mixed results can be partly explained by the fact that it is very hard to define an adequate and representative quantitative measure for the CSR concept (Belu & Manescu, 2013). According to Cavaco and Crifo (2014), another explanation for the contradictory results is the numerous biases and problems in previous work such as model misspecification, omitted variables in the determinants of profitability, limited data, and problems of measurements of CSR and the diversity of measures used to assess financial performance.

2.1.2 ESG and corporate financial performance

In comparison to CSR, ESG is a much newer term as it was first used in 2005 (Kell, 2018). Even though ESG as a term is relatively new the search for the relationship between environmental, social, and governance criteria and CFP dates back to the 1970s (Friede, Busch, & Bassen, 2015). According to Kiron, Kruschwitz, Haanaes, and von Strong Velken (2012), the clear majority of companies view sustainability as a necessary component of being competitive in the marketplace and that sustainability is contributing to the company's profitability. Therefore, a growing number of companies are reporting on their ESG performance. There are fewer research papers on the aggregated effect of ESG on CFP than there are on the relationship between CSR and CFP (Fulton et al., 2012). There are, however, many studies focusing on the individual components of the ESG factors and their influence on CFP. The most researched factor is the governance factor and the least researched factor is the social, as the social factor is the hardest to quantify (Fulton et al., 2012). Previous empiric research studying the relationship between ESG and CFP often include ESG ratings from one or more database such as KLD, Refinitiv (previously ASSET 4), or Bloomberg (Halbritter & Dorfleitner 2015). An ESG portfolio approach is often used where companies are sorted into portfolios based on their ESG performance after which a Fama and French (1993, 2015) or Carhart (1997) multifactor model is used to estimating the abnormal returns of the constructed portfolios (Halbritter & Dorfleitner 2015).

Landlier and Nair (2009) demonstrate that companies with high performance in terms of ESG outperform their conventional peers. Using the KLD database, they pick 150 responsible companies that are included in the S&P 500. After comparing the performance of their portfolio with the S&P 500 they found that the responsible portfolio had slightly superior average returns and only marginally more risk despite having 70% less stocks in the portfolio. Similar to Landlier and Nair (2009), Lee et al. (2013) and Statman and Glushkov (2009) find that companies with high ESG scores overperform companies with low ESG scores. Most of these studies focus on the existence of the correlation instead of the causality. Mănescu (2011) used data on seven ESG attributes for a long panel of large publicly traded US firms during July 1992-June 2008 and found that only community relations have had a positive effect on risk-adjusted stock returns. Furthermore, he found that the effect was not compensation for risk but could be due to mispricing. In the meta-analysis of Friede et al. (2015) which includes 2000 studies, approximately 90% of these studies report a nonnegative ESG-CFP relation. This result suggests that investors can gain positive abnormal returns by trading high and low rated ESG portfolios.

The positive correlation between ESG scores and CFP is not found in all studies. Halbritter and Dorfleitner (2015) investigate the link between companies based on ESG and CFP using ESG data of ASSET 4, Bloomberg, and KLD for the US market from 1991-2012. They use the Carhart 4-factor model and Fama and MacBeth regressions. They do not find a significant difference in returns of companies with high and low ESG ratings. Since they use multiple rating providers, they find that the magnitude and impact of the ESG scores are substantially dependent on the rating provider, the company sample, and the particular subperiod. Another study that did not find a significant relationship between high or low ESG ratings and CFP is that of Auer and Schuhmacher (2016). They use ESG ratings in the Asia Pacific region, United States, and Europe and find that regardless of geographic region, industry, or ESG criterion, active selection of high- or low- rated stocks or portfolios do not provide superior risk-adjusted performance in comparison to a passive investment strategy.

Capelle-Blancard and Petit (2019) use a slightly different approach in their study as they focus on ESG news and Stock market reaction. Their empirical analysis is based on 33,000 pieces of positive or negative ESG news that focus on 100 companies. Firms facing negative events experience a drop in their market value of 0.1% on average, while not experiencing any gains, on average, from positive announcements. Furthermore, market participants are responsive to the media but do not react to firms' press releases. The reputation of the sector that the company belongs also plays a role in the magnitude of the impact.

To summarize the above findings of various CSR and ESG studies the majority reports a positive or nonnegative relationship between CSR and ESG and CFP. This observation is further validated by Fulton et al. (2012) who report the findings of 56 research papers, 2 literature reviews, and 4 meta-studies on this matter. The results show that CSR and ESG factors correlated with superior risk-adjusted returns at a securities level. All of the included academic studies agreed that companies with high ratings for CSR and ESG factors have a lower cost of capital in terms of debt and equity. The market then recognizes that these companies are of lower risk than other companies and rewards them accordingly. 89% of the studies also showed that companies with high ESG ratings exhibit market-based outperformance, while 85% of the studies show accounting-based outperformance, which indicates that the market is showing a correlation between financial performance of companies and advantageous ESG strategies. The strategy of investing in high performing companies in terms of ESG pays off over the medium (3-5 years) to long term (5-10 years). Fulton et al. (2012) further report the key findings concerning the E, S, and G components. The environmental factor is expected to offer stock return potential for investors through first-mover advantage. Early recognition of environmental concerns, carbon regulation, and energy efficiency will potentially help investors transform environmental legislation into opportunities. The social factor is the most difficult factor to quantify. Investing in human capital, health, safety, and social considerations might be a source for generating excess returns. The governance factor has been studied the most and has been strongly linked to a company's cost of equity and debt capital. Due to the factor's early integration into mainstream investing the factor may already be priced into the market.

2.2 Corporate political donations and corporate financial performance

Corporations can donate money to political parties and candidates through four different channels: donations to Political Action Committees (PACs), donations from individuals who list the corporation as their employer, soft money donations, and donations to 527 groups (Aggerwal, Meschke, & Wang, 2012). On average, corporate contributions do not help companies influence voting outcomes (Cooper, Gulen, & Ovtchinnikov, 2010) but companies donate to political parties and candidates for political office because they have an economic interest in various legislative actions, regulatory decisions, or other political outcomes (Aggerwal et al., 2012).

There is less research about the effect corporate political donations (CPD) have on CFP than there is about the social performance and CFP relationship. There are two conflicting arguments that reoccur in the majority of the studies concerning the relationship between CPD and CFP. The first is that political donations represent an investment in political capital that can generate positive returns to the company. The second argument is that political donations can reflect a manager's personal political view, therefore creating an agency problem and possibly creating a cost for the shareholders (Aggerwal et al., 2012). According to prior literature on the subject researches often use short-term event studies to examine the effect of political donations on firm returns (Aggerwal et al., 2012).

Cooper et al. (2010) researched the relationship between CPD and CFP by developing a database of firm-level contributions to U.S. political campaigns from 1979 to 2004 and constructing variables that measure the extent of firm support for candidates which are significantly correlated with the cross-section of future returns. Through a panel regression of annual abnormal returns on the lagged number of supported candidates and other control variables like book-to-market, firm capitalization, and momentum, they find that the number of supported candidates has a statistically significant positive relation with future returns. There are also stronger effects for firms whose contributions are concentrated towards House candidates and Democrats (Cooper et al., 2010). Other studies that provide similar evidence consistent with the value enhancement that political donations have on a company are those of Faccio and Parsley (2009) and Goldman, Rocholl, & So (2009). The studies support the view that there is a negative effect on the firm value when the politicians that the firm donated to lose power but on the other hand the effect on firm value is positive if the politicians get elected.

Aggerwal et al. (2012) investigate if political donations are investments in political capital that should, in expectation, generate positive returns for the firm and its shareholders. The political donations can also be a symptom of agency problems inside a company, as managers donate according to their political preference, which should therefore lower the financial returns of a company. The data of the study consists of corporate donations to political candidates for federal offices in the U.S. between 1991 – 2004. In contrast to previously described studies, Aggerwal et al. (2012) use long-term (one-year) stock returns instead of short-term returns. The results indicate that political donations are negatively correlated with stock returns. A $10,000 increase in donations is associated with a reduction of annual excess return of 7.4 basis points. Poor corporate governance is also associated with larger donations. In addition, donating firms engage in more acquisitions which have significantly lower cumulative abnormal announcement returns than non-donating firms. According to Aggerwal et al. (2012), there is no support for the hypothesis that political donations represent an investment in political capital but instead, donations are symptoms of agency problems within companies. Similarly to Aggerwal et al. (2012), Liang and Renneboog (2017) and Faccio (2010) also concluded that political donations do not appear to enhance shareholder value, but rather tend to reflect agency problems inside the firm.

2.3 Political views and CSR

Many studies have investigated the relationship between corporate social performance and CFP and the relationship between CPD and CFP separately. However, few studies are investigating the combined effects that CPD and CSR have on the financial performance of a company.

Di Giuli and Kostovetsky (2014) research the link between Republican, and Democratic companies and CSR scores. They used the CSR rating of KLD, and find that firms have higher CSR scores when they have Democratic founders, CEOs, and directors. The CSR scores are also dependent on where the headquarters of the companies are situated. Companies with headquarters in Democratic-leaning states tend to have higher CSR scores than companies in Republican-leaning states. They also find that Democratic-leaning firms spend $20 million more or around 10% on net income on CSR than Republican-leaning firms. There is no evidence that the companies recover these expenses through increased sales, indicating that an increase in a firm's CSR rating is associated with negative future stock returns and a decline in return on assets. The results suggest that any benefits from CSR come at the expense of firm value. Similar to Di Giuli and Kostovetsky (2014), Rubin (2008) also discovered in his empirical analysis of the relationship between CSR and political beliefs in the US, that companies with a high CSR rating tend to be located in Democratic (blue) states and counties while companies with low CSR rating tend to be located in Republican (red) states and counties.

3 Hypothesis development

The increased political focus on sustainability combined with companies and investors' acknowledgment of the importance of the subject, has inspired us to investigate if investors can gain from the relationship between the financial and social performance of companies. Previous literature indicates that a positive relationship between social and financial performance exists. There is also research suggesting a correlation between corporate donations and financial performance. The relationship between corporate social performance and corporate political donations is not mutually exclusive as the political beliefs of a company influences their corporate strategies, for example, investment in CSR. This thesis contributes to research on social performance and political beliefs on the financial performance of companies.

We find inspiration in the article "Money where their mouths are" (The Economist, 2019) (hereafter referred to as the reference article). The reference article investigates if there is a relationship between the social liberalism of companies and corporate political donations. They find that even socially liberal companies prefer to donate to the Republican Party, but not as much as their less socially liberal peers do. We find this result interesting and want to investigate this relationship further.

We set up a wokeness index as an indicator of social performance, which combines ESG scores, ESG Controversies score (hereafter referred to as Controversies score), and corporate political donations. We expect that a high ESG score has a positive effect on financial performance while a low Controversies score has a negative effect on financial performance. However, we are not certain how the donations will affect the financial performance of a company, as Republicans tend to prioritize the economy over social and environmental issues which might lead to regulations that benefit companies' financial performance. On the other hand, Democrats try to incorporate these issues into their policies to avoid the costly effects of global warming. To investigate the relationship between the wokeness index and financial performance we want to test the following main hypothesis.

(H 1) Woke companies have higher excess returns than their less woke peers

To investigate the relationship found by the reference article we test the following sub hypothesis:

(SH 1) Woke companies are more likely to donate to the Democrats

To test if the wokeness portfolios need to be rebalanced over time we investigate the consistency of the wokeness scores by testing the following sub hypothesis:

(SH 2) The wokeness score of a company is consistent through time

Lastly, to see how woke portfolios perform compared to the market we develop the following sub hypothesis:

(SH 3) Woke companies have higher excess returns than the market

We estimate the excess returns of the portfolios using Fama and French (1993) 3-factor model, the Carhart (1997) 4-factor model, and the Fama and French (2015) 5-factor model. We construct graphs to illustrate the relationship between wokeness scores and corporate political donations. In addition, we use heatmaps to visualize the consistency of the wokeness scores.

4 Methodology

This section contains a description of the data used in our analysis and the applied econometric framework.

4.1 The wokeness index

Our method is largely inspired by the reference article where a wokeness index is constructed to measure how woke companies are. In the article, the least woke companies get a score of 0 and the wokest companies get a score of 10. The score distribution is as follows; companies score 1-5 points based on CSR scores from Just Capital. Companies can score 1-4 points if one or more of the following briefs are signed: a brief supporting same-sex marriage, a brief supporting transgender bathroom rights, a brief opposing Trumps' travel ban, or a brief seeking to end the gender pay gap. The number of points depends on how many briefs a company signs, each brief is worth one point. The final point is assigned to companies where 60% of employees have donated to the Democratic Party in the 2016 election cycle.

Despite trying to imitate the reference article as closely as possible, we decided to make some changes to our wokeness index. We use the same point distribution for our wokeness index as the reference article, however, we make some changes in the data that we use for the different categories. Instead of CSR scores from Just Capital we use ESG scores from Refinitiv. The CSR scores from Just Capital are based on a weighted model which is determined yearly by Just Capital's polling of the American public (Just Capital, 2020). As we are doing our analysis as a time series, we need a CSR score that is consistent over time and based on more factors in addition to those of Just Capital.

Instead of rewarding companies with a point for each signed brief, we give points to companies based on the controversies they have had each year. We use the Controversies score to assign points to companies. This change is made as the Controversies score gives a broader view of the companies actions and is consistent over time.

The reference article gives one point if a company's employees have donated over 60% to the Democrats. However, the publicly available data for employee donations shows many inconsistencies in the company names, therefore, we do not rely on this data. Instead we resort to the company donations data provided by Center for Responsive Politics as a mean of assigning the political donation score.

4.1.1 Quantifying social responsibility

Several databases provide a framework for quantifying the social responsibility of a company. Amongst the most popular are KLD Research & Analytics by MSCI and Refinitiv by Thomson Reuters. The demand for measuring more than economic factors has increased since the beginning of 1990 as the general interest for sustainability and therefore sustainable investing has increased. KLD was the first agency to start quantifying sustainability and other agencies followed at the beginning of 2000. Since KLD was first on the market they offer the most extensive database with more than 4200 rated companies in the US, while Refinitiv's data covers more than 1100 firms in the US (Halbritter & Dorfleitner, 2015).

The different agencies have different strengths as the data is collected differently, however it is difficult to decide which is better as the measurement criteria are all subjective. KLD collects ESG data based on 70 selected binary indicators for strengths and concerns related to the categories shown in Table (Dorfleitner, Halbritter, & Nguyen, 2015). Refinitiv collects ESG data points for more than 250 Key Performance Indicators' (KPIs). The KPIs are then combined into the three ESG pillars and a total score. Each pillar can attain any value between 0 and 100 (Refinitiv, 2019).

Previous literature that examines the relationship between CSR data and political donation data for companies has used the KLD database to quantify CSR (Di Giuli & Kostovetsky, 2014, and Cooper et al., 2010). When comparing financial performance with CSR scores previous research has used a larger variety of databases, including Refinitiv and Sustainalytics (Halbritter & Dorfleitner, 2015). As the KLD data is unavailable we resort to a different database, namely Refinitiv. The Refinitiv score gives the option to include a controversies score that controls for any public controversies the companies have been involved in.

To be able to understand how our results might differ from previous studies combining CSR and political donations data we examine the main differences between Refinitiv and KLD data. Halbritter and Dorfleitner (2015) provide a comparison of the main CSR databases.

Table 1 shows the main measurement criteria for Refinitiv and KLD. Examining the table, it is clear that the measurement criteria for the two databases are slightly different but related to the same subjects. For example, in the social pillar, Refinitiv considers workforce, human rights, community, and product responsibility, where KLD measures human capital, product liability, stakeholder opposition, and social opportunities. Similarly, Environmental and Governance measures the same concepts, but with slightly different measurement criteria as shown in Table 1. Dorfleitner et al. (2015) examine the quantitative differences between the databases by comparing the descriptive statistics. To be able to compare the two databases they transform the KLD data to a percentage measure. They find that the ESG ratings for KLD and Refinitiv are significantly different in terms of distribution and risk, indicating that comparing the result with previous studies might not be feasible. In a sample of 4356 companies, they find the Refinitiv have an ESG mean of 44.25. In comparison, the KLD has an average ESG of 66.42 in a sample of 5323 companies. In addition, the Refinitiv has a considerably higher standard deviation of 27.14, where KLD shows a standard deviation of only 8.38. This suggests that results using different databases will differ substantially. (Dorfleitner et al., 2015)

Pillars	Refinitiv	KLD
Environmental	Resource use Emissions Innovation	Climate change Natural resources Pollution and waste Environmental opportunities
Social	Workforce Human rights Community Product responsibility	Human capital Product liability Stakeholder opposition Social opportunities
Governance	Management Shareholders CSR strategy	Corporate governance Corporate behavior

Table 1: The main measurement criterions for KLD and Refinitiv

The Refinitiv score is collected as a weighted average of three overall pillars, which are divided into a total of 10 categories. Each of the 10 categories is calculated based on a large number of indicators. The information for each pillar is measured based on publicly available information on the rated company (Refinitiv, 2019). Refinitiv (2019) assigns higher weights to more mature indicators. This means that higher weights are assigned to categories with more disclosed information, resulting in higher transparency being rewarded. For example, management has a high degree of transparency as composition, diversity, independence, committees, etc. can be measured. CSR strategy is given a lower weight as it is difficult to objectively measure (Refinitiv, 2019). Weight and the number of indicators used in the rating are given in Table 2.

Pillar	Category	Indicators in Rating	Weights	Piller Weights
Environmental	Resource use	19	11%	34%
	Emissons	22	12%	
	Innovation	20	11%	
Social	Workforce	29	16%	35.5%
	Human rights	8	4.5%	
	Community	14	8%	
	Product responsibility	12	7%	
Governance	Management	34	19%	30.5%
	Shareholders	12	7%	
	CSR strategy	8	4.5%	
Total		178	100%	

Table 2: Weights assigned to each pillar and category (source: Refinitiv, 2019)

The Controversies score is measured based on 23 controversy topics. The Controversies score is calculated based on global media coverage capturing all information related to negative events like lawsuits, ongoing legislation, disputes, and fines (Refinitiv, 2019). The Controversies score allows us to control for events that oppose the ESG score. A Controversies score of 100 indicates that a company has had no controversies during the year. The more controversies a company has, the lower the Controversies score will be for the given year.

4.1.2 Data Collection

4.1.2.1 The ESG Score

The ESG scores are collected from Refinitiv for the years 2004 to 2019. ESG data is usually disclosed yearly based on publicly available information, such as annual reports. As Refinitiv does not disclose when it updates the scores, we simply use the year end scores. We limit our data to include the S&P 500 as this is the only index that Refinitiv has calculated ESG scores for since 2004. As indicated in Table 3, 498 of the 500 companies in the S&P 500 had an ESG score available in 2019 while only 236 companies were rated in 2004. We exclude 2004 from our analysis as ESG scores are not available for the election cycle 2003-2004. We have also excluded 2019 as the political election cycle 2019-2020 is still ongoing. The reason why we do not have data for all 500 companies is that we use the companies included in the S&P 500 in 2020 as a baseline for company selection.

Year	Number of rated companies	Year	Number of rated companies
2019	498	2011	440
2018	494	2010	428
2017	493	2009	408
2016	489	2008	371
2015	471	2007	354
2014	457	2006	342
2013	451	2005	300
2012	449	2004	236

Table 3: Number of rated companies in a given year from 2004-2019

Figure 1 shows the average, the highest, and the lowest ESG score for all years in the dataset. The average ESG score is indicated by the dark blue line that is increasing over time. This means that, on average, companies have a higher ESG score in 2019 compared to earlier. This is well-aligned with the increased focus on sustainability that is seen in society through this period. The green line shows the highest ESG score in any given year. The trend for this is not clear like the average score, it fluctuates between 88 in 2004-2005 and 98 in 2010-2011. The light blue line is the lowest score for a given year. This line shows no trend as it fluctuates between a score of 24 in 2004 and a score of 7 in 2019. Figure 1 indicates that the scores are more equally distributed in the earlier years, while the distribution is skewed towards higher scores in later years.

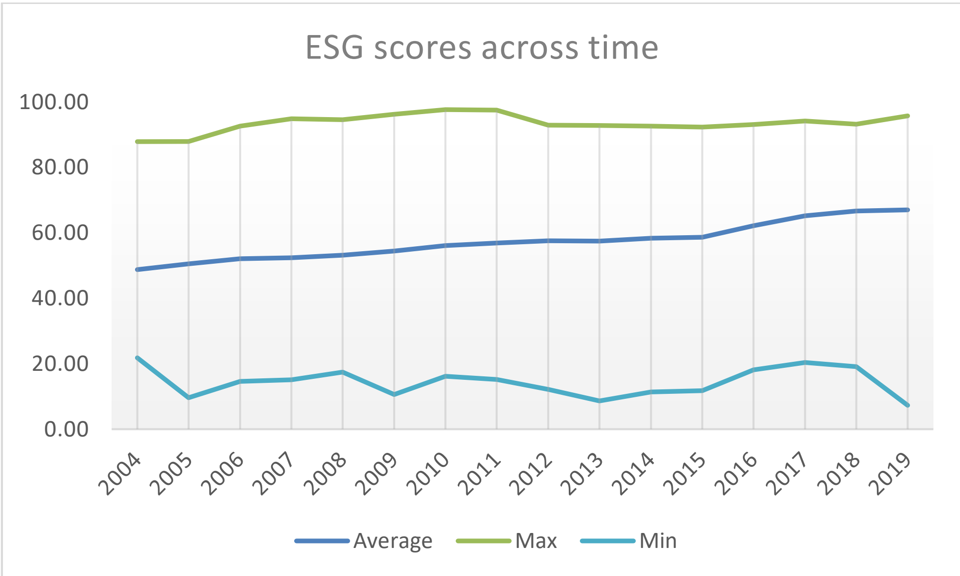

Figure 1: Descriptive statistics for ESG scores across time

Figure 2 shows the distribution of ESG scores in 2018 and Figure 3 shows the distribution in 2005. In 2018 the distribution is skewed to the right as most companies received a score in the interval

[71.90, 78.50], which is higher than the mean score of 66.71. In 2005 the scores are more centered towards the middle with a mean score of 50.57.

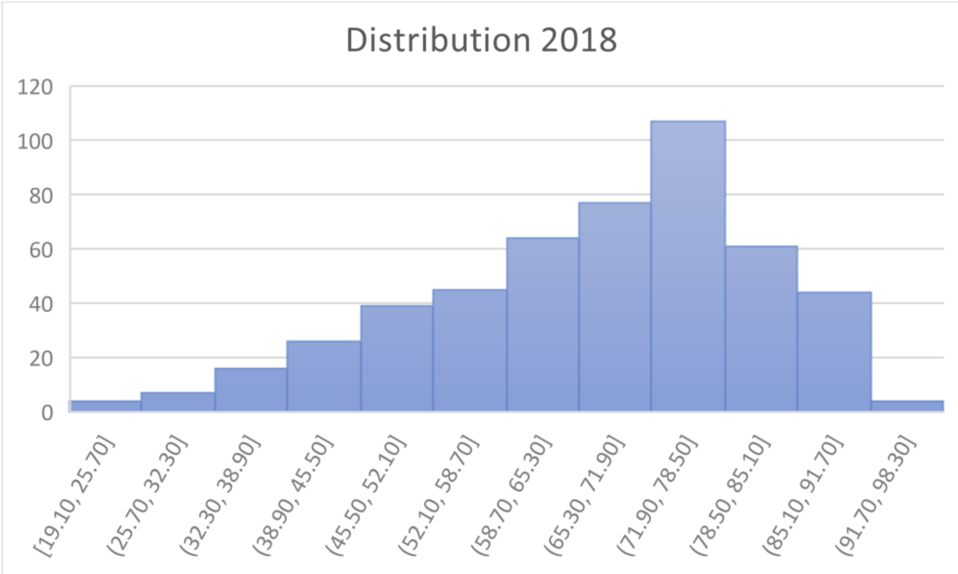

Figure 2: Distribution of ESG score in 2018

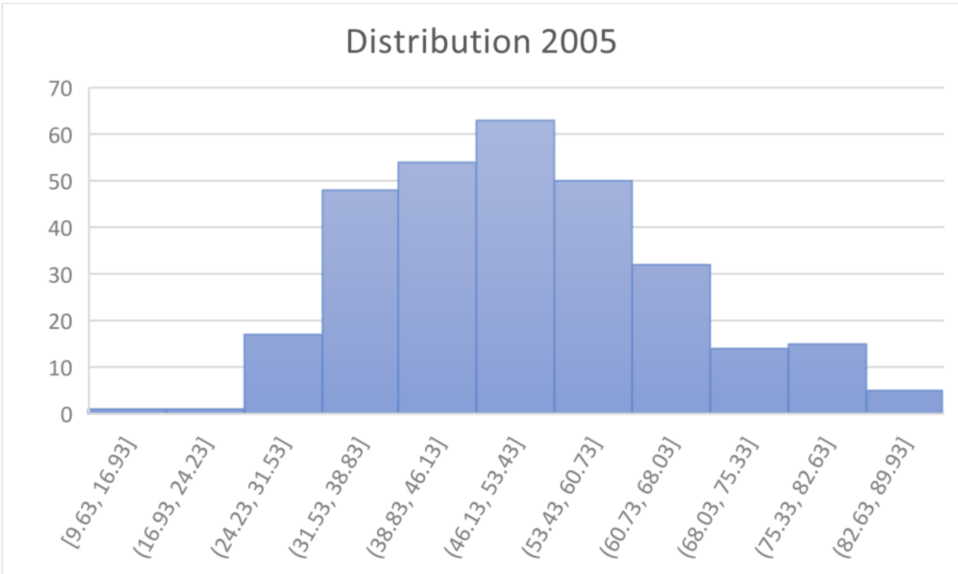

Figure 3: Distribution of ESG scores in 2005

4.1.2.2 The Controversies score

The Controversies score is collected from Refinitiv from 2004 to 2019 for S&P 500 companies. The Controversies score is updated continuously as controversies occur, hence we use the year end score. As the score is collected for the same companies as the ESG score, the number of companies we have a rating for is the same. However, the distribution of the scores is different. Figure 4 shows the minimum, mean, and highest Controversies score, color-coded the same way as in Figure 1. Unlike the ESG score, the average and maximum Controversies scores are decreasing over time, while the minimum scores are approximately 0 for all years. This indicates that companies are increasing their ESG score, while at the same time being subject to more controversies. Unlike the ESG scores the distribution of Controversies scores is skewed towards a higher score in the earlier years.

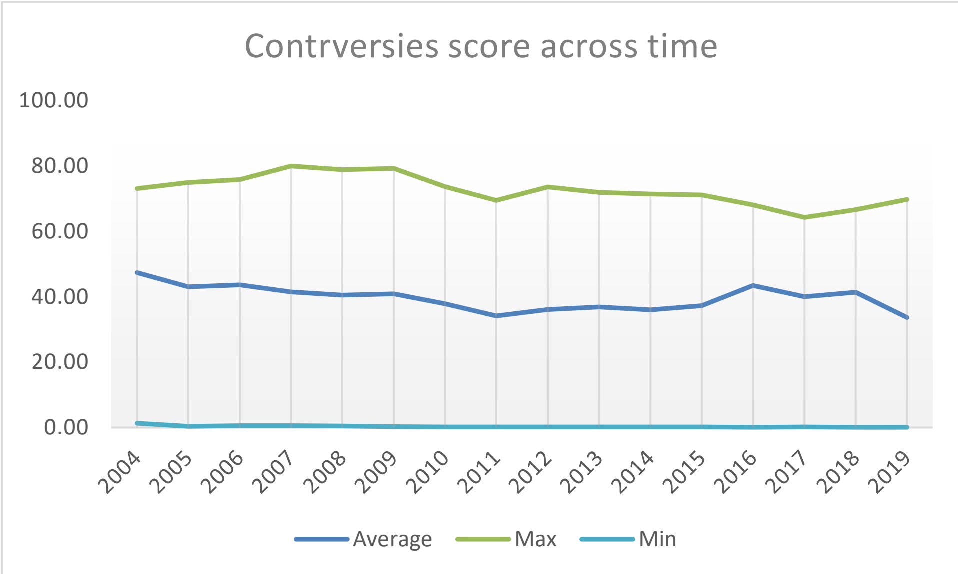

Figure 4: Descriptive statistics for the Controversies scores across time

4.1.2.3 Data for corporate political donations

We obtain the data for corporate political donations from the Center for Responsible Politics which is a nonpartisan, independent, and nonprofit research group tracking money in U.S. politics and its effect on elections and public policy (Center for Responsive Politics, 2020). Most other papers on political donations and the reference article use the same source for political data. We reached out to the Center for Responsive Politics and asked for all donations made by U.S. companies. We specifically requested for the total donations made by each company, the amount donated to the Republican party, and the amount donated to the Democratic party. The data consists of company donations from the election cycle 2006 to cycle 2018, and as each cycle is 2 years long the data covers 7 cycles in total. The reason for not collecting data prior to the 2006 election cycle is that there is hardly any ESG-data available before 2004.

The data we received is structured in six columns: election cycle year, rank (1 is given to the company that has donated most), organization name, the total amount donated, amount donated to Democrats and Liberals, and lastly amount donated to Republicans and Conservatives.

Cycle	# of donators	Total donations (in millions)	Average all donations	Total to Dem & Lib (in millions)	Average to Dem & Lib	Total to Rep & Cons (in millions)	Average to Rep & Cons
2018	19,289	$2,919	$151,327	$1 550	$80,335	$1,321	$68,470
2016	19,486	$3,380	$173,477	$1 683	$86,352	$1,702	$87,347
2014	17,676	$1,713	$96,933	$855	$48,389	$851	$48,153
2012	21,188	$2,316	$109,329	$970	$45,802	$1,333	$62,919
2010	5,409	$636	$17,548	$347	$64,127	$272	$50,202
2008	22,980	$1,654	$71,955	$970	$42,194	$682	$29,667
2006	18,647	$1,089	$58,397	$521	$27,937	$553	$29,675

Table 4: The number of companies that donated in any given political cycle, total amount of donation in each election cycle, average amount of donations in each election cycle, total and average donations to Democrats and Liberals, and total and average donations to Republicans and Conservatives

We have summarized the data in Table 4. The number of companies donating to a political party is between 17,000 and 23,000 each year except in 2010 where there was a major decrease in the number of companies donating. The number of companies donating tends to be a bit higher during election cycles with a presidential election. We can also observe that the average amount donated seems to be higher during cycles with a presidential election. The donations also seem to be increasing slightly over time excluding the election cycle 2010. There is no clear pattern which political party receives most of the donations.

Election cycle	# of S&P 500 companies that donated	Majority to Dem & Lib	Majority to Rep & Cons
2018	431	196	235
2016	425	157	268
2014	416	119	297
2012	414	115	299
2010	285	136	149
2008	404	201	203
2006	397	115	282

Table 5: Total number of S&P 500 companies that have donated in a given cycle, number of companies that donated most to the Democrats and Liberals, and number of companies that donated most to the Republicans and Conservatives.

For the purpose of our analysis, we transform the dataset to only include the S&P 500 companies and their donations for each year. In Table 5 we summarize the total number of companies that have made at least one donation to a political party. In addition, we summarize if the companies donated mostly to the Democrats and Liberals or the Republicans and Conservatives. None of the election cycles include donations from all S&P 500 companies. In general, the number of companies that donated is between 400 and 500, except in 2010 when the amount of donating companies decreased to around 300. This corresponds with Table 5, which shows that the total donations are considerably lower in 2010 than any other cycle. For all election cycles, there is an overweight of companies that donated mostly to the Republicans and Conservatives.

Election Cycle	Average total	Average to Dem & Lib	Average to Rep & Cons
2018	$798,672	$337,872	$423,711
2016	$880,880	$345,921	$530,747
2014	$523,247	$197,890	$321,905
2012	$627,893	$231,493	$396,173
2010	$413,737	$192,498	$218,453
2008	$483,904	$252,191	$231,156
2006	$354,236	$131,478	$218,087
Total	$510,321	$241,335	$334,319

Table 6: Average amount donated by companies in the S&P 500.

From Table 6: Average amount donated by companies in the S&P 500.6 we see that the average amount donated by S&P 500 companies generally increases over the years. The average donations seem to increase more during election cycles with a presidential election. The average amount donated to the Republicans and Conservatives is higher than the average amount donated to the Democrats and Liberals which corresponds with the donation trend that we see in Table 4.

4.1.2.4 State color

In our analysis, we are interested in seeing how the voting preference of the companies' home state affects the donations of companies. The term blue state refers to a state where the majority of people vote for the Democratic presidential candidate and a red state refers to a state where the majority of people vote for the Republican presidential candidate. In the reference article, they found that if a company's headquarters are in a blue state the company tends to donate more to democrats than companies that have their headquarters in a red state.

We gather the state color of the 50 states from Politico (2016). Since the previous presidential election was in 2016, we use 2016 as our baseline year for the state colors. There are 20 blue states and 30 red states. The distribution of the state colors can be found in Table 7 below.

Alabama	Hawaii	Massachusetts	New Mexico	South Dakota
Alaska	Idaho	Michigan	New York	Tennessee
Arizona	Illinois	Minnesota	North Carolina	Texas
Arkansas	Indiana	Mississippi	North Dakota	Utah
California	Iowa	Missouri	Ohio	Vermont
Colorado	Kansas	Montana	Oklahoma	Virginia
Connecticut	Kentucky	Nebraska	Oregon	Washington
Delaware	Louisiana	Nevada	Pennsylvania	West Virginia
Florida	Maine	New Hampshire	Rhode Island	Wisconsin
Georgia	Maryland	New Jersey	South Carolina	Wyoming

Table 7: Distribution of red and blue states

4.1.3 Forming the wokeness index

The wokeness index is based on the three pillars described above: ESG score, ESG controversies score, and the corporate political donations. We set up two different wokeness indices to examine if they yield similar results as the reference article. The indices are based on the same data but structured differently. The first woke index is solely based on integer values. The second index is based on continuous values, and each component can obtain any value in a given interval.

4.1.3.1 The Integer wokeness index

To imitate the reference article as closely as possible we convert the ESG scores into points from 1-5, assigned as shown in Table 8.

ESG score	Points assigned
80-100	5
60-79.99	4
40-59.99	3
20-39.99	2
0-19.99	1

Table 8: ESG score converted to points

Furthermore, we assign points from 0-4 based on the Controversies score. As we want to make our analysis comparable to the reference article, we build the index to match the number of points assigned. We include zero as we do not believe that companies with Controversies score below 20 should be assigned any points. Also, the distribution in Figure 4: Descriptive statistics for the Controversies scores across time, shows that the minimum score assigned each year is approximately 0, where the minimum for the ESG score (Figure 1) between 7 and 24. We want the points we assign to reflect the score in the article, as we want it to be comparable. The points are assigned according to the table below.

ESG Controversies score	Points assigned
80-100	4
60-79.99	3
40-59.99	2
20-39.99	1
0-19.99	0

Table 9: Controversies score converted to points

In the third category, political donations, we assign 1 point to companies that have donated over 50% to the Democrats as Democrats are known to be more socially liberal. The threshold that we use for assigning the point is lower than in the reference article as they assign 1 point to companies where employees have donated over 60% to the Democrats. As shown in Table 5 more companies donated to the Republicans and Conservatives, which is why we find it justifiable to lower the donation threshold to 50%.

To summarize this index, the minimum score a company can be assigned is 1, and the highest score is 10. The distribution of scores in 2018 is shown in Figure 5.

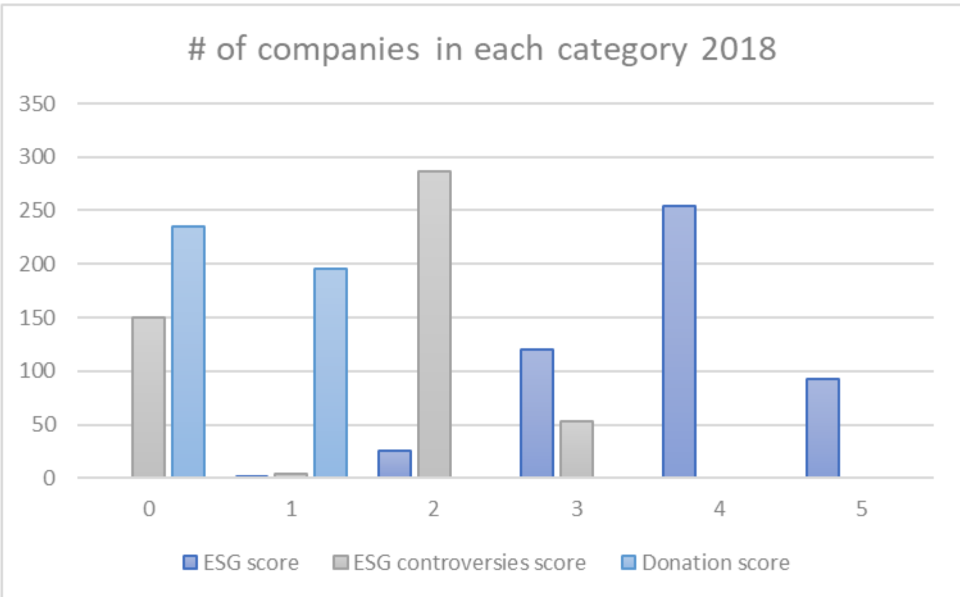

Figure 5: Number of companies that received a given point in each category (2018 data)

From Figure 5 we see that in 2018 most companies have been assigned 4 points in the ESG score category and that almost no companies receive below 3 points. This indicates that most companies in the S&P 500 take ESG matters into consideration in their strategies. For the Controversies score most companies have been assigned 2 points, and no companies receive above 3 points, suggesting that all companies have controversies. In the donation category, the majority of companies have 0 points assigned as we also see in Table 5.

The total wokeness score is the sum of the points assigned to each company in the three categories. Figure 6 shows the distribution of the total scores for 2018 in a histogram. The most frequent score is 6, which is assigned to 154 companies. 98% of companies have received a score between 3 and 8. The wokeness scores seem to be relatively normally distributed in this year, indicating that the index is constructed fairly.

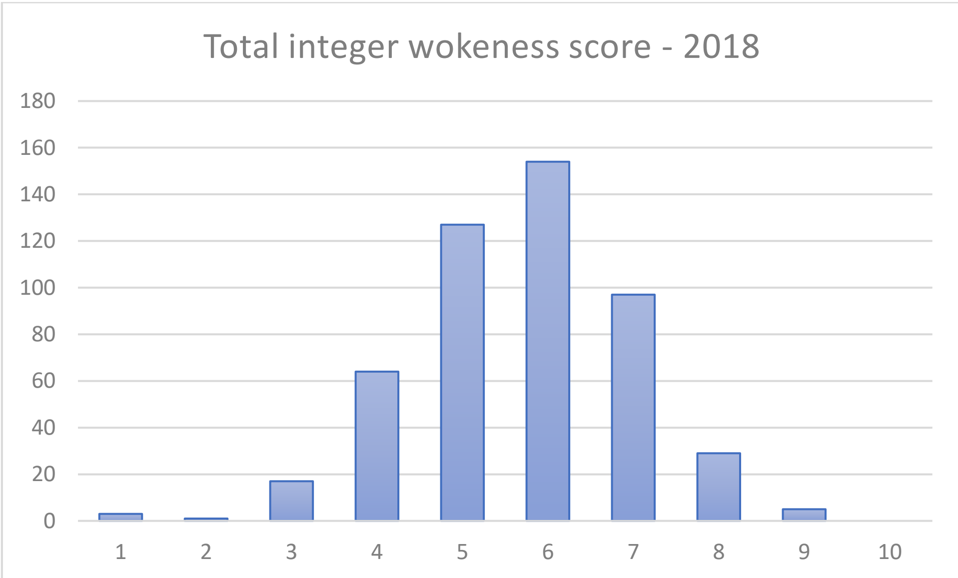

Figure 6: Number of companies that received a given total score (2018 data)

4.1.3.2 The continuous wokeness index

The continuous index is set up like the integer index. We use the same number of points in each category, but instead of assigning whole numbers to fixed intervals we simply modify the scores to be continuous. For example, for the ESG category, a company with an ESG score of 78.32 is assigned 78.32/10/2= 3.92 points. In the continuous index, we do not fix values below a certain level to 0, as the score should reflect the continuity the different categories have. The interval for the Controversies score is 0-4, and the interval for the political donations are 0-1.

Figure 7 shows the distribution of the total wokeness score for the continuous index for 2018. The majority of the companies have received a score in the interval (5.00,6.00] closely followed by the lower interval (4-00,5.00]. The total scores are in general lower compared to the integer index, and it seems that the spread across scores is lower.

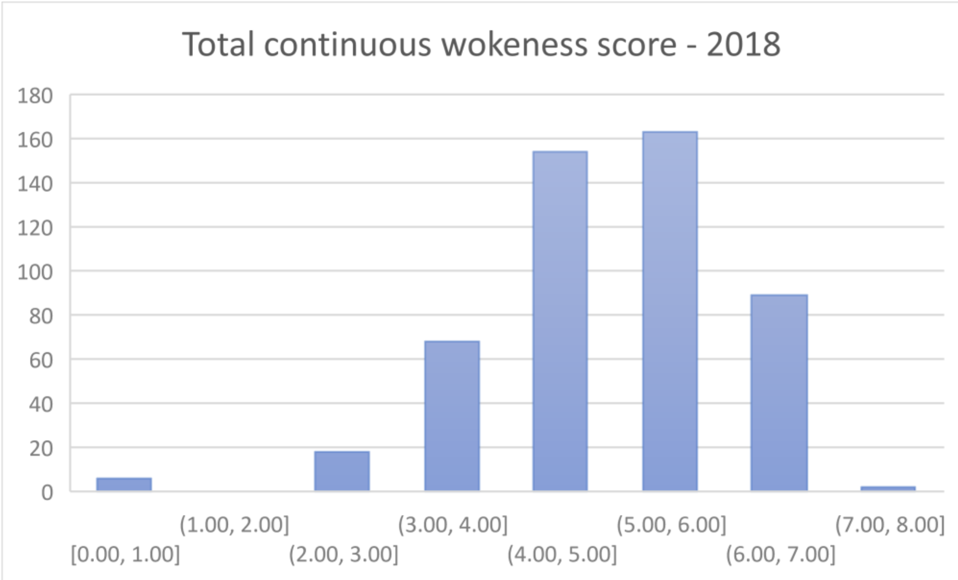

Figure 7: Number of companies that received total score in a given interval (2018 data)

Figure 8 shows the distribution of wokeness scores across time. The average wokeness score seems to decrease slightly over time, unlike the ESG score in Figure 1. Even though the highest weight is on the ESG score, the index is not just replicating this score. The distribution of wokeness scores in each year seems to be similar to the one we see for 2018 in Figure 7.

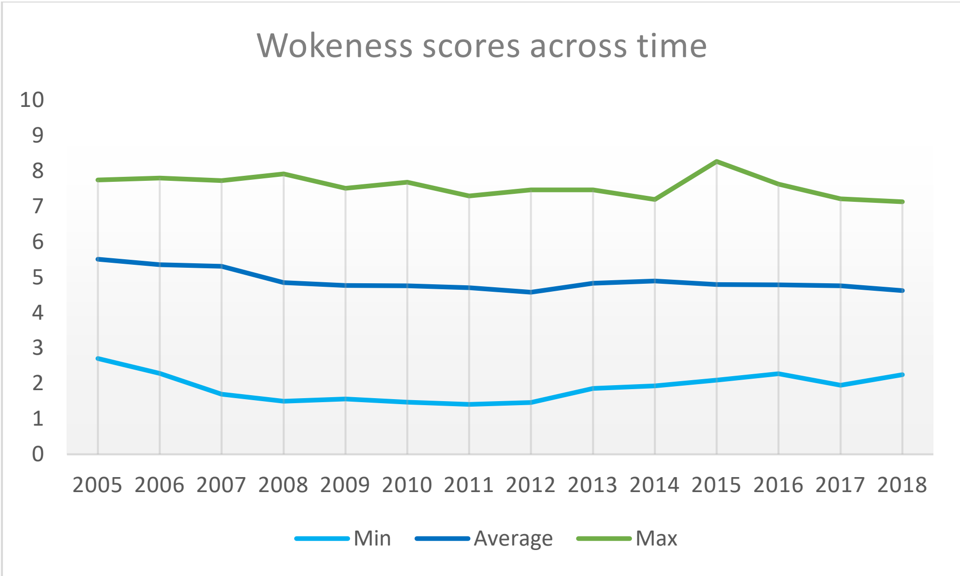

Figure 8: The maximum score, the average score, and the minimum score assigned in each year.

Figure 9 shows the distribution of wokeness scores in 2018 for different selected industries. The continuous scores are transferred into integers for easier visualization. For example, if the score is 3, it contains all scores between 2 and 3. We see from the figure that most consumer-facing companies have scores between 4 and 5, which is lower than the most common score for the total distribution in Figure 7. This industry also has more companies than any other industry. Health care and technology show the same pattern as the consumer-facing industry. The patterns for finance, energy and utility are similar to each other and they mostly have companies with a score between 6 and 7. Industrial has the most even distribution with the highest number of companies scoring between 5 and 6. Figure 9 indicates that the finance and energy and utility industries are more woke than other industries. However, the finance industry have no scores above 7, where all other industries are represented. The technology industry is known to focus more on sustainability, but our wokeness index indicates that the distribution for this industry is skewed to the left in 2018.

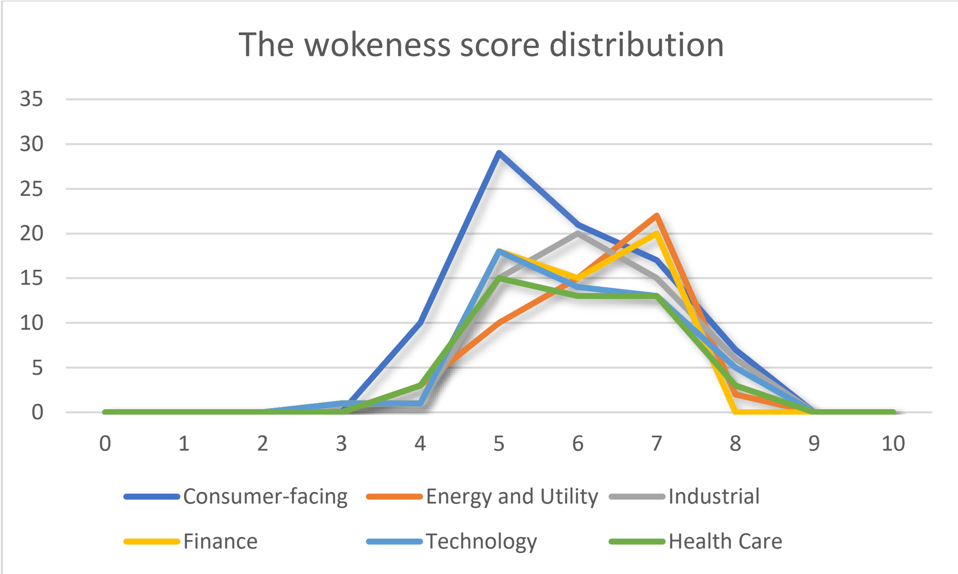

Figure 9: The wokeness score distribution for 2018 based on different industries. The horizontal axis indicate the wokeness score and the vertical axis is the number of companies.

To check the consistency of the wokeness score through time, we plot the average score for each industry in Table 10 below. The table shows a trend that all industries improve their average score over time and in particular in 2016-2018. Finance has lower average scores than any other industry and the industry with the highest average scores is technology.

	Energy and Utility	Industrials	Finance	Consumer-facing	Healthcare	Technology
2018	5.64	5.62	5.47	5.31	5.50	5.54
2017	5.33	5.29	5.26	5.30	5.45	5.51
2016	5.25	5.16	5.09	5.34	5.55	5.61
2015	4.88	4.83	4.52	4.80	5.17	5.12
2014	4.86	4.60	4.44	4.85	4.90	5.16
2013	4.94	4.59	4.34	4.75	4.85	5.16
2012	5.06	4.73	4.33	4.64	4.97	4.95
2011	4.71	4.39	4.20	4.66	4.84	5.03
2010	5.27	4.72	4.61	4.59	4.90	4.80
2009	5.04	4.82	4.74	4.92	5.05	4.67
2008	4.97	4.64	4.52	4.97	4.72	5.12
2007	4.87	4.73	4.45	4.84	5.02	4.86
2006	4.99	4.53	4.64	4.64	4.74	5.01
2005	4.55	4.36	4.45	4.53	4.93	5.03
Total	**5.03**	**4.79**	**4.65**	**4.87**	**5.04**	**5.11**

Table 10: Average wokeness score for the years 2005-2018, sorted according to industry.

To further investigate the wokeness score, we look at the distribution of the separate scores in 2018. We select two industries with different distributions. Looking at the donation score, energy and utility has a clear overweight of companies that donated mostly to the Republicans, where technology has a clear overweight of companies that donated mostly to the Democrats. This indicates that the technology industry is more woke in its political views. Companies in the technology industry mostly have an ESG score between 3 and 5, while in energy and utility most companies have a score of 4. The distribution indicates that companies in technology have a slightly higher average ESG score. On the other hand, close to 25 companies in technology have a low Controversies score of 2 indicating a high amount of controversies despite the high ESG score. In the energy and utility industry, fewer than 15 companies have a Controversies score of 2, which likely leads to a higher total score.

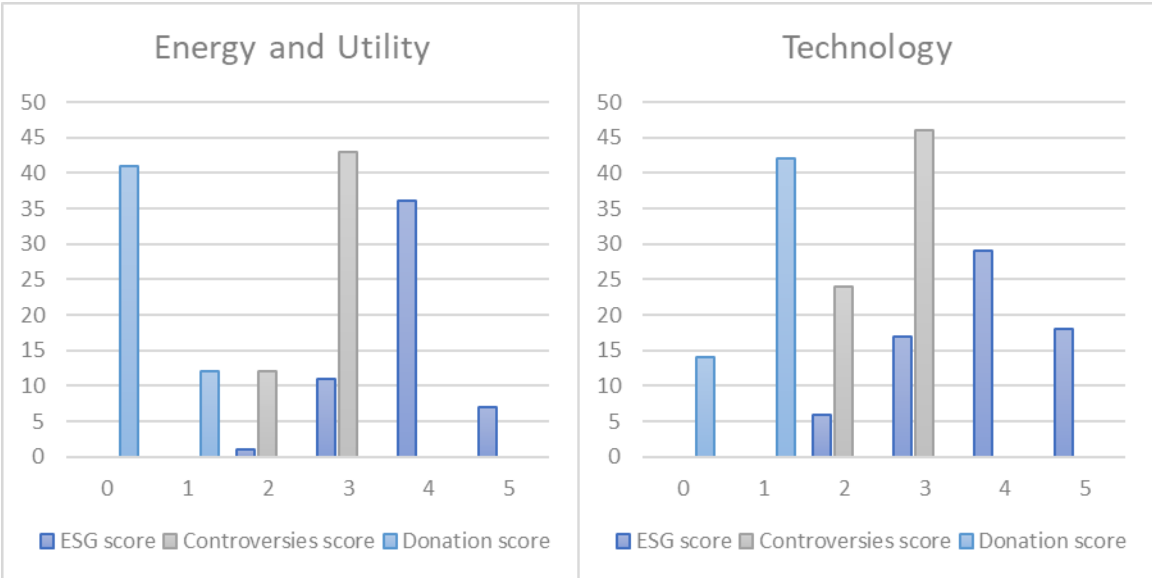

Figure 10: The distribution of ESG scores, Controversies score and donation score for technology, energy and utility in 2018.

4.1.4 Forming the wokeness portfolios

After setting up the wokeness index we form our wokeness portfolios. To form the portfolios we download data from Thomson Reuters Datastream that include the following information; RIC ticker, the company name, the state where the headquarter of the company is situated, the industry (Global Industry Classification Standard), the market cap, and the monthly returns for the period January 2006 to December 2019.

We exclude all companies which have no data on; financial returns, donations, ESG score, Controversies score, or market cap. The number of the remaining companies each year can be seen in Table 11. The table also shows the number of companies with headquarter in blue (hereafter referred to as blue companies) and red (hereafter referred to as red companies) states respectively.

Year	# of companies	Blue companies	Red companies
2018	404	230	174
2017	406	232	174
2016	400	228	172
2015	390	220	170
2014	378	215	163
2013	376	214	162
2012	374	210	164
2011	368	205	163
2010	254	142	112
2009	248	138	110
2008	310	176	134
2007	296	166	130
2006	298	170	128
2005	264	144	120

Table 11: Number of companies included in the wokeness index, divided into number of red and blue companies from 2005-2018

After excluding companies with insufficient data, we sort the remaining companies into wokeness portfolios based on their wokeness score. The portfolios are rebalanced yearly according to wokeness score. Transaction costs are not considered in the formation and rebalancing of portfolios. We construct four different portfolio scenarios to investigate the performance of the companies in the wokeness index. In the first scenario, we construct three portfolios sorted based on the wokeness index. The first portfolio includes the companies with the 15% highest wokeness scores (hereafter referred to as top 15). The second portfolio includes the companies with the 15% lowest wokeness scores (hereafter referred to as bottom 15), the third portfolio includes the remaining 70% of the companies (hereafter referred to as neutral 70). In the second scenario, we divide the companies into intervals of 25% based on the wokeness index. We then get four equally sized portfolios: 0-25, 25-50, 50-75, 75-100, where the 0-25 is the portfolio with the lowest-scoring companies and 75-100 is the portfolios with the highest-scoring companies. In the third scenario, we divide the companies into the 30% lowest-scoring companies (hereafter referred to as bottom 30), the 30% highest-scoring companies (hereafter referred to as top 30), and the remaining 40% of the companies (hereafter referred to as neutral 40). In the fourth scenario we divide the companies into two equally sized portfolios; the 50% lowest-scoring companies (hereafter referred to as bottom 50) and the 50% highest-scoring companies (hereafter referred to as top 50).

All of the portfolios are value weighted according to the companies' market cap. We use the weights to calculate the weighted average return for each month in the period 2006-2019. Since we use the year-end ESG and Controversies scores, we lag the returns by 1 month. Meaning that we use the returns for 2006 when sorting the wokeness scores for 2005. The reason for the lagged returns is that we want to analyze returns from an investor's point of view, hence all information in the wokeness index needs to be publicly available for any effect to show in the returns.

To further test the sensitivity of our results we use the same portfolio scenarios a second time but instead of value weighting the returns in the portfolios according to each company's market cap we weigh each company in the portfolio equally.

We examine each of the portfolios to see if there are any clear trends in the characteristics of the companies included in the wokeness portfolios.

Year	Blue Companies			Red Companies		
	Bottom 15	Neutral 70	Top 15	Bottom 15	Neutral 70	Top 15
2018	41.70%	56.70%	73.30%	58.30%	43.30%	26.70%
2017	42.60%	56.10%	77.00%	57.40%	43.90%	23.00%
2016	60.00%	52.30%	75.00%	40.00%	47.70%	25.00%
2015	43.10%	56.00%	70.70%	56.90%	44.00%	29.30%
2014	48.20%	56.60%	67.90%	51.80%	43.40%	32.10%
2013	55.40%	56.80%	58.90%	44.60%	43.20%	41.10%
2012	44.60%	58.20%	57.10%	55.40%	41.80%	42.90%
2011	49.10%	54.30%	69.10%	50.90%	45.70%	30.90%
2010	63.20%	54.50%	55.30%	36.80%	45.50%	44.70%
2009	62.20%	53.70%	56.80%	37.80%	46.30%	43.20%
2008	43.50%	58.30%	63.00%	56.50%	41.70%	37.00%
2007	52.30%	56.90%	56.80%	47.70%	43.10%	43.20%
2006	56.80%	57.10%	56.80%	43.20%	42.90%	43.20%
2005	48.70%	54.50%	64.10%	51.30%	45.50%	35.90%

Table 12 shows the distribution of red and blue companies for the bottom 15 neutral 70 and top 15 portfolios. Even though Table 11 shows that there are more blue companies overall, Table 10 indicates an overrepresentation of red companies in the bottom portfolios and a higher number of blue companies in the top portfolios.

Year	Blue Companies			Red Companies		
	Bottom 15	Neutral 70	Top 15	Bottom 15	Neutral 70	Top 15
2018	41.70%	56.70%	73.30%	58.30%	43.30%	26.70%
2017	42.60%	56.10%	77.00%	57.40%	43.90%	23.00%

2016	60.00%	52.30%	75.00%	40.00%	47.70%	25.00%
2015	43.10%	56.00%	70.70%	56.90%	44.00%	29.30%
2014	48.20%	56.60%	67.90%	51.80%	43.40%	32.10%
2013	55.40%	56.80%	58.90%	44.60%	43.20%	41.10%
2012	44.60%	58.20%	57.10%	55.40%	41.80%	42.90%
2011	49.10%	54.30%	69.10%	50.90%	45.70%	30.90%
2010	63.20%	54.50%	55.30%	36.80%	45.50%	44.70%
2009	62.20%	53.70%	56.80%	37.80%	46.30%	43.20%
2008	43.50%	58.30%	63.00%	56.50%	41.70%	37.00%
2007	52.30%	56.90%	56.80%	47.70%	43.10%	43.20%
2006	56.80%	57.10%	56.80%	43.20%	42.90%	43.20%
2005	48.70%	54.50%	64.10%	51.30%	45.50%	35.90%

Table 12: The percentage amount of blue and red companies in the bottom 15, neutral 70, and top 15.

We can see the same trend in the other portfolio scenarios as well (Table 14 and Table 13), the blue portfolios dominate the top portfolios and the red companies are more frequent in the majority of the bottom portfolios. From scenario 2 we see that the middle portfolios show a different trend in recent years. The 25-50 portfolio is dominated by blue companies, while the 50-75 portfolios is dominated by red companies.

	Blue companies				Red companies			
Year	0-25	25-50	50-75	75-100	0-25	25-50	50-75	75-100
2018	50.0%	66.7%	43.1%	68.6%	50.0%	33.3%	56.9%	31.4%
2017	45.1%	67.6%	45.1%	72.5%	54.9%	33.3%	55.9%	27.5%
2016	51.5%	60.4%	41.6%	74.3%	48.5%	39.6%	58.4%	25.7%
2015	45.9%	58.2%	59.2%	63.3%	54.1%	42.9%	41.8%	36.7%
2014	49.5%	56.3%	62.1%	62.1%	50.5%	44.2%	38.9%	37.9%
2013	50.5%	54.7%	61.1%	62.1%	49.5%	45.3%	38.9%	37.9%
2012	42.6%	62.8%	66.0%	54.3%	57.4%	38.3%	35.1%	45.7%
2011	43.0%	52.7%	65.6%	62.4%	57.0%	47.3%	34.4%	37.6%
2010	59.4%	48.4%	67.2%	51.6%	40.6%	51.6%	32.8%	48.4%
2009	57.1%	55.6%	57.1%	54.0%	42.9%	44.4%	42.9%	46.0%
2008	49.4%	48.1%	74.0%	57.1%	50.6%	53.2%	27.3%	41.6%
2007	58.7%	50.7%	57.3%	58.7%	41.3%	49.3%	42.7%	41.3%
2006	50.7%	54.7%	61.3%	64.0%	49.3%	46.7%	40.0%	36.0%
2005	47.8%	50.7%	61.2%	61.2%	52.2%	49.3%	38.8%	38.8%

Table 13: The percentage amount of blue and red companies in the intervals; 0-25, 25-50, 50-75, and 75-100

Year	Blue companies			Red companies			Blue Companies		Red companies	
	Bottom 30	Neutral 40	Top 30	Bottom 30	Neutral 40	Top 30	Bottom 50	Top 50	Bottom 50	Top 50
2018	52.1%	56.8%	62.0%	47.9%	43.2%	38.0%	57.9%	55.9%	42.1%	44.1%
2017	46.7%	58.3%	66.4%	53.3%	41.7%	33.6%	55.7%	58.6%	44.3%	41.4%
2016	52.5%	51.6%	68.3%	47.5%	48.4%	31.7%	56.0%	58.0%	44.0%	42.0%
2015	47.0%	61.1%	59.0%	53.0%	38.9%	41.0%	51.8%	61.0%	48.2%	39.0%
2014	49.6%	58.8%	61.9%	50.4%	41.2%	38.1%	52.9%	60.8%	47.1%	39.2%
2013	49.1%	59.9%	60.7%	50.9%	40.1%	39.3%	52.7%	61.2%	47.3%	38.8%
2012	42.9%	66.2%	55.4%	57.1%	33.8%	44.6%	52.4%	59.9%	47.6%	40.1%
2011	44.5%	59.5%	61.8%	55.5%	40.5%	38.2%	47.3%	64.1%	52.7%	35.9%
2010	56.6%	57.8%	52.6%	43.4%	42.2%	47.4%	54.3%	57.5%	45.7%	42.5%
2009	54.1%	57.4%	54.1%	45.9%	42.6%	45.9%	56.5%	54.8%	43.5%	45.2%
2008	50.5%	58.9%	60.2%	49.5%	41.1%	39.8%	48.4%	65.2%	51.6%	34.8%
2007	58.4%	52.1%	59.6%	41.6%	47.9%	40.4%	54.1%	58.1%	45.9%	41.9%
2006	52.8%	58.3%	59.6%	47.2%	41.7%	40.4%	52.3%	61.7%	47.7%	38.3%
2005	49.4%	53.3%	62.0%	50.6%	46.7%	38.0%	48.5%	60.6%	51.5%	39.4%

Table 14: The percentage amount of blue and red companies in the bottom 30, neutral 40, and top 30 and the bottom 50 and top 50.

Further, we notice that the companies vary in size. Table 15 shows the average market cap in each portfolio for scenarios 1, 3, and 4. The table clearly indicates that the top portfolios have a lower market cap on average. The trend is more pronounced in more recent years. The values tend to get more extreme as the portfolio size increases. This might indicate that big companies are less woke.

Average market cap (in millions)								
Year	Bottom 15	Neutral 40	Top 15	Bottom 30	Neutral 40	Top 30	Bottom 50	Top 50
2019	47,721	52,943	37,513	69,007	50,636	29,728	73,869	25,883
2018	48,072	59,568	42,474	66,309	60,946	36,692	74,317	36,155
2017	54,982	52,391	47,375	70,394	47,799	39,337	67,706	36,272
2016	40,220	53,734	26,101	55,291	57,884	26,212	60,772	34,422
2015	39,164	44,702	25,376	41,350	50,650	27,678	47,726	34,294
2014	37,900	45,660	30,615	48,025	47,585	29,280	53,871	30,655
2013	31,947	41,465	25,190	44,790	38,592	27,235	46,188	28,992
2012	27,208	36,704	17,948	26,250	45,284	21,487	39,675	25,287
2011	38,980	39,850	17,272	43,265	46,588	15,667	45,557	27,127
2010	30,955	38,130	18,430	45,129	35,600	21,147	43,341	24,858
2009	18,383	30,122	20,828	27,274	31,538	19,912	28,747	25,255
2008	17,564	19,254	18,294	18,877	18,088	19,881	21,998	15,704
2007	27,733	28,579	42,743	31,119	27,411	34,198	31,554	29,537
2006	37,716	34,974	31,756	52,000	28,702	26,208	43,991	25,749

Table 15: Average market cap of each portfolio in scenario 1, 3, and 4.

4.2 Econometric framework

We are interested in examining the financial impact of the wokeness index. We use Fama and French's 3-factor model (Fama & French, 1993), the Carhart 4-factor model (Carhart, 1997), and the Fama and French 5-factor model (Fama & French, 2015) to compare returns of the wokeness portfolios.

4.2.1 Fama and French 3-factor

The 3-factor model is an extension of the CAPM by Sharpe (1964) and Lintner (1965). The 3-factor model captures the relationship between average return and size of companies, and the relationship between average return and price ratios, such as book-to-market ratio (Fama & French, 1993). The Fama and French (1993) 3-factor model is given by the following equation.

$$r_i - r_f = \alpha_i + b_i\mathrm{MktRF} + s_i SMB + h_i HML + \epsilon_i$$

Where:

- $r_i - r_f$ is expected excess return for company *i*
- α_i is the constant alpha
- $MktRF$ is the excess return on the market portfolio

- SMB is the size premium
- HML is the value premium
- $b_i, s_i \; and \; h_i$ are the factor coefficients

Fama and French (1993) defined three risk factors that affect stock returns: the overall market factor, a size premium factor, and a value premium factor (book-to-market ratio). The factors are denoted SMB (small minus big size), HML (High minus low book-to-market), and MktRF (market excess return).

We define the market to be the same as the market defined by Kenneth R. French (2020), hence we simply use the pre-calculated factors available on Kenneth R. French data library (French, 2020). The factors in this library are formed based on all stocks in the NYSE, AMEX, and NASDAQ indices. The stock data has been collected from the CRSP database. The market return is defined as all stocks "…listed on the NYSE, AMEX, or NASDAQ that have a CRSP share code of 10 or 11 at the beginning of month t, good shares, and price data at the beginning of t, and good return data for t…" (French, 2020). The risk-free rate is the one-month Treasury bill rate from Ibbotson Associates.

When interpreting the coefficients, we refer to the market coefficient as beta and the other coefficients as the coefficient for HML and SMB. The alpha captures the return not explained by the market or the other factors i.e. the excess return. Hence, we use alpha to compare the performance of our portfolios. The beta coefficient measures the portfolios exposure to the systematic market risk. If beta is one the portfolio has the same exposure to risk as the market. A beta under one (over one) indicates lower (higher) exposure to market risk (Campbell, Lo, & MacKinlay, 1997). The coefficient SMB is related to market size of the companies and should capture the fact that small companies historically have outperformed big companies. A SMB coefficient below (above) 0 indicates that the portfolio consists mostly of large (small) cap companies. The coefficient HML is related to book-to-market and captures the fact that companies with high book-to-market have historically outperformed companies with low book-to-market. An HML coefficient below (above) 0 indicates that the portfolio has an overweight of growth (value) companies. (Fama & French, 1993)

4.2.2 Carhart 4-factor model

The Carhart 4-factor model is an extension of the Fama and French 3-factor model. In addition to the existing three factors, a momentum factor, MOM, is added to the model. The MOM factor captures the tendency for the stock price to continue rising when it is increasing and to continue declining when the price of the stock is decreasing (Carhart, 1997). This model allows investors to assume predictive value of the prior return of stocks. The Carhart (1997) 4-factor model is given by the following equation:

$$r_i - r_f = \alpha_i + b_i \text{MktRF} + s_i SMB + h_i HML + m_i MOM + \epsilon_i$$

Where:

- $r_i - r_f$ is expected excess return for company *i*
- α_i is the constant alpha
- $MktRF$ is the excess return on the market portfolio
- SMB is the size premium
- HML is the value premium
- MOM is the momentum premium
- $b_i, s_i, h_i,$ and m_i are the factor coefficients

The data for MOM is retrieved from the Kenneth R. French data library (French, 2020). A MOM coefficient below (above) 0 indicates that there is an overweight of continuously decreasing (increasing) stocks in the portfolio (Carhart, 1997). The data and the interpretation for the other factors are the same as for the 3-factor model.

4.2.3 Fama and French 5-factor model

In 2015 Fama and French proposed an expansion to the 3-factor model. The 5-factor model includes two new factors; the profitability factor and the investment factor. The profitability factor (RMW) is defined as the difference between the returns of firms with high and low operating profitability (robust minus weak). The investment factor (CMA) is the difference between the returns of firms that invest conservatively and firms that invest aggressively (Fama & French, 2015). The Fama and French (2015) 5-factor model is given by the following equation:

$$r_i - r_f = \alpha_i + b_i \text{MktRF} + s_i SMB + h_i HML + r_i \text{RMW} + c_i \text{CMA} + \epsilon_i$$

Where:

- $r_i - r_f$ is expected excess return for company *i*
- α_i is the constant alpha
- $MktRF$ is the excess return on the market portfolio

- SMB is the size premium
- HML is the value premium
- RMW is the profitability factor
- CMA is the investment factor
- b_i, s_i, h_i, r_i, and c_i are the factor coefficients

Similar to the other models, we retrieve the data for the factors from the Kenneth R. French data library (2020). The interpretation of the factor coefficients we know from the 3-factor model are the same. An RMW coefficient below (above) 0 suggests an overweight of weak (robust) companies in the portfolio. A CMA coefficient below (above) 0 indicates an overweight of aggressive (conservative) companies in the portfolio. (Fama & French, 2015)

4.2.4 OLS regression

The ordinary least squares (OLS) is a parameter estimation method in a linear regression model, where estimation is achieved by minimizing the square distance between data and model parameters (Hamilton, 2004). The methodology of using the OLS framework in asset pricing is inspired by Campbell, Lo & MacKinlay (1997).

In our analysis, we consider multiple predictor variables with the purpose of explaining the correlation of wokeness scores and monthly portfolio performance. The multiple regression is mathematically expressed as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_n x_{in} + \epsilon_i$$

Where:

- β_0 is the intercept, and indicates the expected value of y when all the x's are 0
- β_{i1} is the slope coefficient on x_{i1} or simple the coefficient

To conduct a multiple regression, certain assumptions must be made. According to Stock and Watson (2015), there are four least square assumptions in the multiple regression model:

1. ϵ_i has a mean of zero. Meaning that y_i sometimes is above the regression line and sometimes below, but on average y_i is on the regression line. This is the main assumption for insuring unbiased estimators.
2. $x_{i1}, x_{i2}, \dots, x_{in}, y_i$ are independently and identically distributed (IID) random variables. This assumption is related to how the sample is drawn. In asset pricing we assume the returns follow a random walk (Campbell, Lo, & MacKinlay, 1997).
3. Large outliers are unlikely.
4. There is no perfect multicollinearity, which means that none of the regressors can be perfectly correlated.

The R-squared measures the fraction of the sample variance of y that is explained by the regressors. Hence, R-squared is expressed in a range from 0% to 100%, where higher values indicate that more variance is explained. The R-squared value increases whenever an additional regressor is added, unless the coefficient of the regressor is exactly zero. To avoid false improvement in the model when adding additional regressors, we use the adjusted R-squared to assess the fit of the model. The adjusted R-squared accounts for multiple factors by adding a degree-of-freedom-correction to the traditional R-squared calculation. (Stock & Watson, 2015)

As we are investigating the excess return of the wokeness portfolios, we want to ensure that the intercept (the alpha) is statistically different from zero. This hypothesis is tested using a statistical test that tests if the coefficient is different from zero. We test the null hypothesis H0: the coefficient is 0, against the alternative hypothesis H1: the coefficient is different from 0. The tests are mutually exclusive, as only one test can be true. (Stock & Watson, 2015)

$$H_0: \beta_i = 0 \text{ vs } H_1: \beta_i \neq 0$$

The test is conducted by computing the t-statistic and comparing this against the 97.5% (double-sided test) value in the students t-distribution, given that we use a 5%-significance level. The p-value is computed using these two inputs and is what we will use to assess the significance of the coefficients. In our analysis, we will use a significance level of 5%. A p-value of 5% indicates that we can be 95% certain the coefficient value is different from 0. (Stock & Watson, 2015)

The confidence intervals are constructed based on the coefficient value and the standard error of the coefficient. The interval indicates a range, where the true value of a coefficient is included with 95% certainty. Coefficients with higher standard error will have wider confidence intervals, and lower standard error leads to narrower confidence intervals.

5 Analysis

In this section, we present the results of our analysis. We start by showing the relationship between the wokeness score and the corporate political donations. Hereafter, we review the consistency of the wokeness scores through time. Lastly, we estimate the financial performance of the wokeness portfolios using graphs and different factor models.

5.1 The integer wokeness graphs

To evaluate if our wokeness index behaves similarly to the index in the reference article, we create similar graphs to the ones seen in the article (Appendix 1). We use these graphs to analyze the connection between the wokeness index, the amount donated to the Democrats, and the political orientation in the state of the companies headquarter. Each of the graphs is constructed with the integer wokeness index on the horizontal axis and the companies' donations to the Democrats measured in percentage along the vertical axis. The blue scatter points represent companies with headquarters in a democratic state (hereafter referred to as blue companies), and the red dots represent companies with headquarters in a republican state (hereafter referred to as red companies). The grey line is a linear regression line based on all companies in the same industry.

The graphs in the reference article are created for five different industries: energy, chemical and others, finance, consumer-facing, health, and technology. We will create graphs for the same industries, with one small difference as we split the energy, chemicals, and other in two, because of the number of companies in this sector. In the reference article, a linear regression is used as a statistical model to explain general differences is wokeness. We use a similar regression to illustrate the trend between wokeness and donations to the Democrats. Table 16 shows the results of the linear regressions for 2018.

Industry	R^2	Intercept	Slope
Energy and Utilities	29.53%	-0.3286	0.1145
Industrials	12.11%	0.0211	0.0672
Finance	1.51%	0.2996	0.0257
Consumer-facing	11.70%	0.1037	0.0738
Healthcare	9.11%	0.2131	0.0538
Technology	8.93%	0.3677	0.0553

Table 16: Statistical model for the integer wokeness index vs share of donations to the Democrats

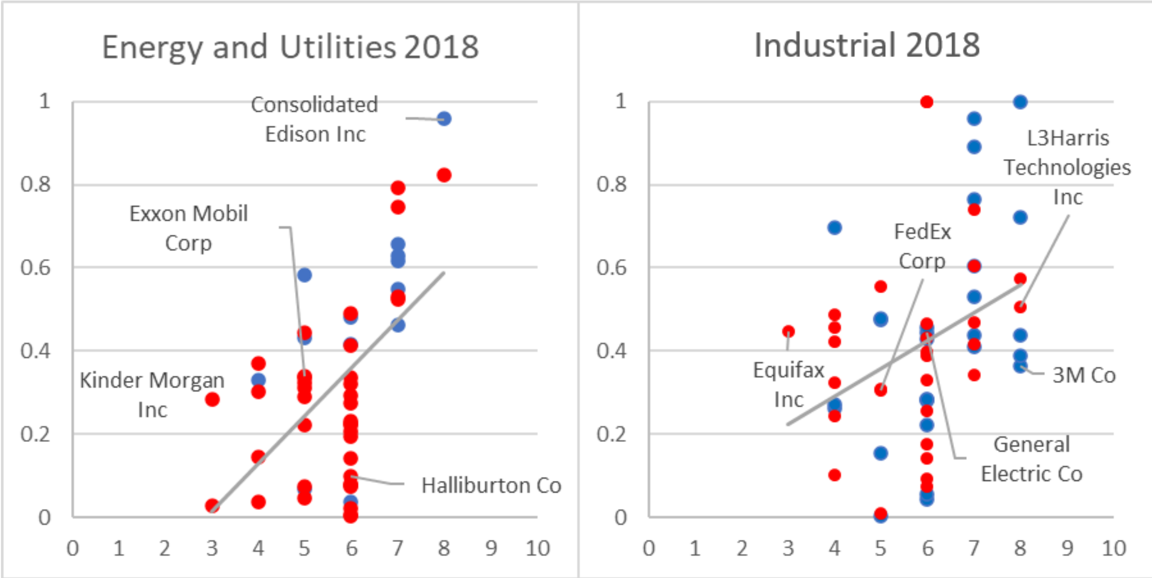

Figure 11: The integer wokeness index vs share of donation given to the Democrats for Energy and Utility industry and Industrials industry in 2018

In Figure 11 we see that the majority of energy and utility companies have their headquarters in Republican states as there is a clear overweight of red dots. The graph indicates a trend, which suggests that when the wokeness score increases the percentage donation to Democrats will also increase. Table 16 shows that the linear regression for energy and utility has an R-squared value of 29.53%, meaning that 29.53% of the variation in the wokeness score is explained by the companies donations to the Democrats. The scatter plot indicates that blue companies are donating more to the Democrats, as the blue dots are, in general, placed higher up in the graph. Only one blue dot is below the trendline. The red scatter points are mainly placed below the 40% donation mark suggesting that the majority of red companies are donating mostly to the Republicans. Companies with a wokeness score of 7 and above tend to donate over 50% to the Democrats. The linear regression for energy and utility in Table 16 tells us that every time the wokeness score is increased by one the given company will donate 11.45% more to the Democrats. This is the only model that has a negative intercept, and also the only model that has a slope above 10%.

The trend for the industrial industry is less clear as shown by the R-squared value of 12.11% which is considerably lower than the R-squared for energy and utilities. Companies with a wokeness score between 3 and 6 mainly donate less than 50% to the Democrats. Companies with a wokeness score above 6 tend to donate more to the Democrats as the scatter points are mainly placed above the 50% donation mark. In this graph, the scatter points seem to be spread more randomly, and there is no clear pattern in the concentration of the colors. The slope of this model is not as steep as the slope for energy and utility as an increase of one in the wokeness score would only yield a 6.72% increase in donations to the Democrats.

The reference article uses a different industry indicator and therefore has one graph for energy, chemicals, and others (see Appendix 1). We use the graphs for energy and utility and industrial in Figure 11 as a comparison to this. The graph in the reference article shows a slightly different pattern as the trendline is very flat and the wokeness scores are, in general, lower which is true for both red and blue companies. The model in the reference article indicates a weak trend that companies with higher wokeness scores tend to be blue and donate more to the Democrats. All red companies donate below 50% to the Democrats and only 6 blue companies are placed above the 50% donation mark.

We compare some of the highlighted companies in our graphs to the corresponding companies in the graphs of the reference article to see if our wokeness indices yield similar scores for the same companies. When comparing the placement of Exxon Mobil Corp and Halliburton we can see that the amount both companies donated to the Democrats is higher in our graph. In the reference article, Halliburton scored between 2 and 3 points while it scored 6 points in our wokeness index. Exxon Mobil scored 5 points in both wokeness indices. General Electric scored 6 points in both indices, however, our graph suggests that General Electric donated over 40% to the Democrats which is slightly more than indicated by the graph in the reference article.

In the finance graph, in Figure 12, we see that a majority of the companies have a wokeness score between 5 and 7. Most companies are blue and mainly placed above the 40% donation mark. However, the trend is very weak as there seems to be no clear trend in the distribution of the scatter points. This is confirmed as the model indicates that an increase of one in wokeness score will yield a 2.57% increase in donations to the Democrats. There are both blue and red companies with low and high wokeness scores and no clear pattern can be found in the donations. It is clear from Table 16 that the model has low explanatory power with an R-squared of 1.51%.

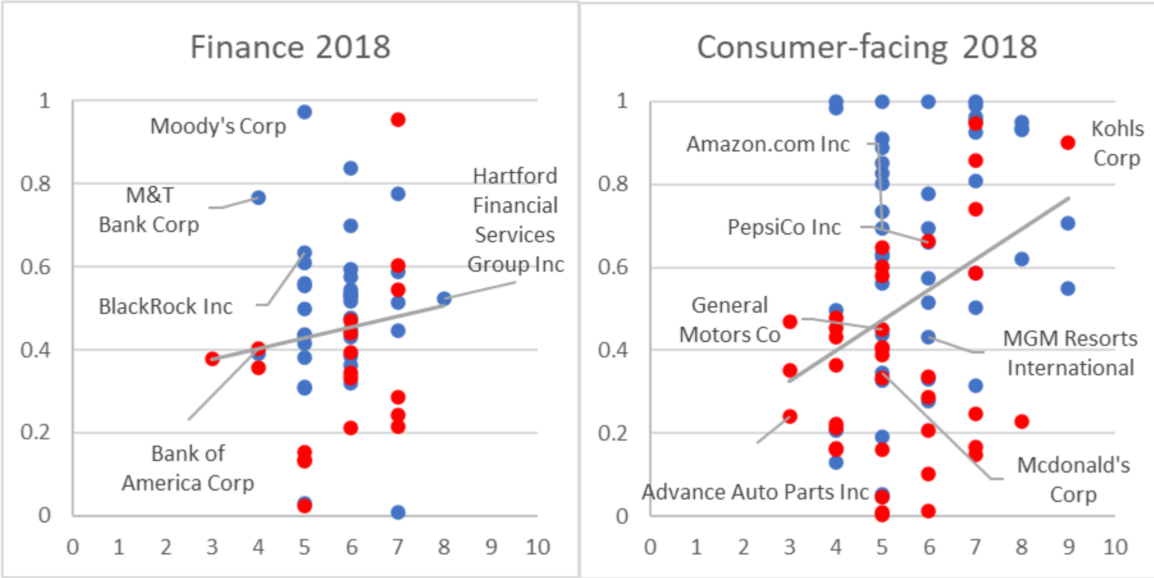

Figure 12: The integer wokeness index vs share of donation given to the Democrats for the Finance industry and Consumer-facing industries in 2018

In the reference article, the finance graph has a similar distribution as the finance graph in Figure 12. Blue companies tend to donate more to the Democrats than red companies. However, the companies are more evenly spread across the wokeness index in the reference article, with scores ranging from 0 to 7. The trendline in the graph for the finance industry is steeper in the reference article compared to the one in our graph for finance suggesting that an increase in wokeness yields a higher percentage increase in donations to the Democrats. The spread across wokeness scores is lower in our finance graph, compared to the finance graph in the reference article, and it seems that our graphs, in general, have higher standard deviation as there is a wider spread in how much companies donate to the Democrats. When comparing the wokeness scores of some companies in our finance graph to the corresponding companies in the finance graph in the article we see that Blackrock scores around one point higher in our wokeness index, however, both graphs report almost the same percentage of donations to the Democrats. Bank of America scores higher according to the reference articles wokeness index as the company's wokeness score is around 7, while the score is only 4 according to our wokeness index. The percentage donated to the Democrats is around 35-40% in both graphs.

In the consumer-facing graph 11.70% of the variation in wokeness scores is explained by the donations. The red companies seem to be placed mainly below the 50% donation mark, where the blue companies are mainly above. However, it is not clear if blue companies tend to have higher wokeness scores. If the wokeness score increases by one, the model suggests that the company will donate 7.38% more to the Democrats.

Compared to the consumer-facing graph, of the reference article, the trendline of our consumer-facing graph is steeper. MGM Resorts and Mc Donald's score higher in our wokeness index with 6 and 5 wokeness points respectively, while they score around 1 and 0 points in the wokeness index of the reference article. PepsiCo and General Motors score 6 and 5 in our wokeness index, respectively, while they score around 8 and 7 points in the reference articles' index. The percentage donated to the Democrats by these companies in the reference article is not consistent with the donations in our graphs.

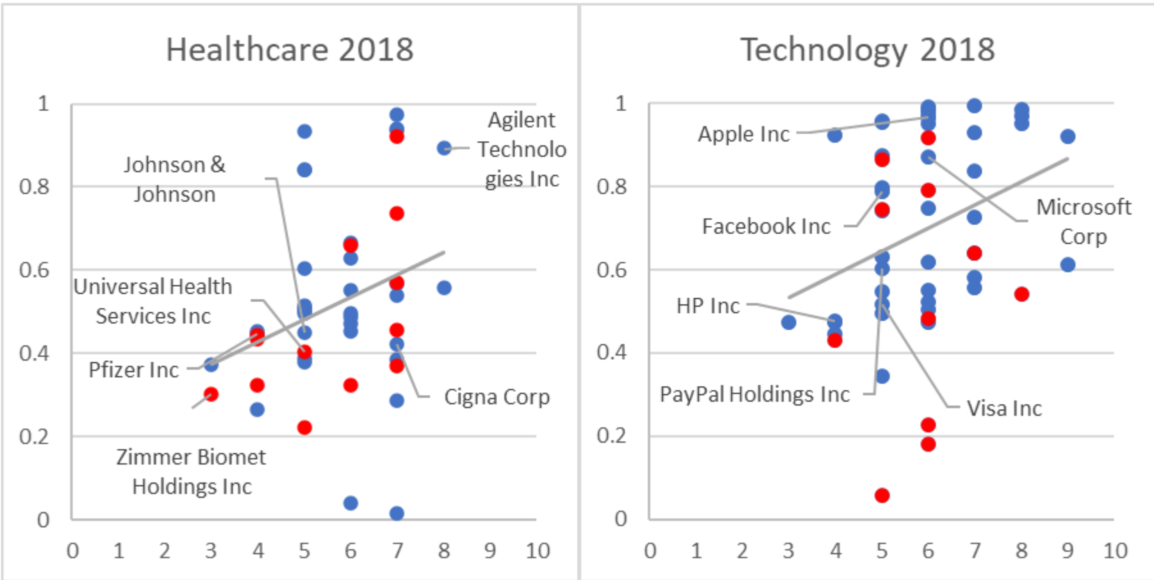

Figure 13: The integer wokeness index vs share of donation given to the Democrats for the Healthcare industry and Technology industry in 2018

In Figure 13, we see that both the healthcare and technology industries mainly consist of blue companies. In the healthcare graph there seems to be a vague trend that an increase in wokeness will increase donation towards Democrats. The trend does not seem to be dependent on the placement of the headquarter as there is no pattern in the color distribution. 9.11% of the differences in wokeness scores is explained by political donations. An increase of one in the wokeness score will yield an increase of 5.38% in donations to the Democrats.

In the technology graph, the distribution of the scatter points seems to indicate that the relative majority of companies with a high wokeness score are blue companies. We see only two red companies with a score of 7 or above. This industry seems to be dominated by blue companies, which, in general, donate more to the Democrats. Compared to the reference article's graphs our graphs are relatively similar, however, our graphs tend to have a higher standard deviation. The intercept in the technology graph is the highest at 36.77% indicating that a company with a wokeness score of 0 would still donate over 35% to the Democrats.

When comparing the wokeness scores of Johnson & Johnson, Cigna, Pfizer, and Universal Healthcare in our healthcare graph to the scores of the corresponding companies in the reference articles' health graph, we cannot see many similarities in the scores. The percentage that these companies donated to the Democrats is not consistent in the graphs either. When comparing the wokeness scores of HP, Facebook, and Paypal in our wokeness index to the wokeness index of the reference article, we notice that the wokeness scores are lower according to our wokeness index. However, in terms of donations to the Democrats, the percentage donated is higher in our graph.

When comparing our graphs to the graphs in the reference article, we notice two general differences. Firstly, the donations to the Democrats never exceed 75% in the article, where our data shows that more companies donate 100% to the Democrats. According to the reference article, only two companies donated 0% to the Democrats, where our data shows more companies with 0% donations to the Democrats. The article uses the Center for Responsive Politics as a source for corporate political donations, which is the same source that we use. As the data was provided to us by a data expert it is hard to control if the data is correct, however, we assume this data is accurate. The reference article shows the majority of companies donated under 50% to the Democrats, but no companies donated above 75%, which seems doubtful. Secondly, when comparing the wokeness scores of the individual companies, we notice that our index yield different scores than the reference article. We suspect that the difference is mainly due to the fact that we punish companies for their controversies. For example, the in reference article Facebook scores around 9 points, while we assign only 5 points, due to the high amount of controversies. Also, the article uses a very narrow measure of wokeness for the 4 extra points. Not signing a brief does not necessarily mean that the company is against the brief.

In the reference article, the wokeness index is continuous, indicating that the CSR scores are assigned as a continuous score. As we are constructing portfolios based on the highest and lowest scoring companies, we want to be able to distinguish between the companies that receive the same score in the integer index. To make this division we construct the continuous wokeness index and construct the same graphs using this index. Comparing the wokeness indices with one another will also test the sensitivity of the model.

5.2 The continuous wokeness graphs

Table 17 shows the linear regression results using the continuous wokeness index. Comparing the regression results of the continuous model with the integer model in Table 16, the explanatory power of the continuous model is generally lower. The difference can be explained by the fact that we assign political donation scores continuously instead of using a cutoff point of 50%.

Industry	R^2	Intercept	Slope
Energy and Utilities	22.89%	-0.3354	0.1171
Industrials	10.44%	0.004	0.0742
Finance	2.35%	0.6128	-0.0328
Consumer-facing	11.89%	0.0241	0.0935
Healthcare	5.66%	0.2342	0.0522
Technology	6.72%	0.3717	0.0584
All industries	5.39%	0.1542	0.0621

Table 17: Statistical model for the continuous wokeness index vs share of donations to the Democrats

Comparing the energy and utilities and industrial graphs in Figure 11 and Figure 14, both graphs are similar in terms of placement of the scatter points and direction of the trendline. Table 17 confirms this when we compare the slope and intercepts of the energy and utilities, and industrials to the models in Table 16. This is further confirmed by comparing the few selected companies. Consolidated Edison has a wokeness score of 8 in the integer index and a wokeness score of 7.38 in the continuous index. Kinder Morgan has a wokeness score of 3 in the integer index and a score of 3.34 in the continuous index. L3 Harris Technologies has a wokeness score of 8 in the integer index, but only a score of 6.20 in the continuous index. The company donated 51% to the Democrats and is assigned a score of 1 in the integer index, but only a score of 0.51 for the donations in the continuous index. The same pattern is seen if the ESG and Controversies scores are close to the assigned cutoff values. This indicates that the integer index might assign too high or too low scores to companies if the scores are close to the selected limits. The wokeness scores of the remaining highlighted companies are very similar.

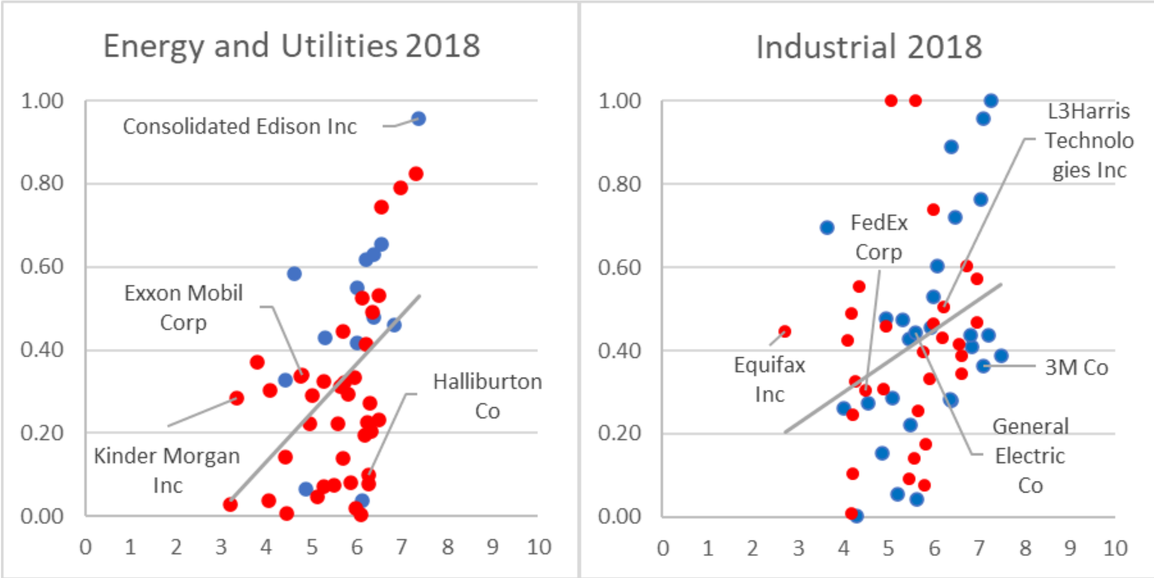

Figure 14: The continuous wokeness index vs share of donation

In the finance graph in Figure 15, the distribution of scatter points looks similar to the finance graph in Figure 12. The blue companies are mainly placed above the trendline and the red companies are mainly below, however the trendline has a negative slope in the continuous model. The model indicates little correlation between the wokeness index and political donations, seen by an R-squared of 2.35% in the continuous model and 1.51% for the integer model.

Companies in the consumer-facing industry are more spread across wokeness scores in the integer graph (Figure 12) compared to the continuous graph (Figure 15). The R-squared is slightly lower at 11.89% in the continuous model compared to 11.70% in the integer model. The intercept is lower and the slope is slightly steeper for the continuous model compared to the integer index. Kohls receive a score of 9 in the integer index and only 7.52 in the continuous index. MGM Resorts is assigned a slightly higher score of 6.56 in the continuous index compared to a score of 6 in the integer index. The remaining highlighted companies have relatively similar scores in the two indices.

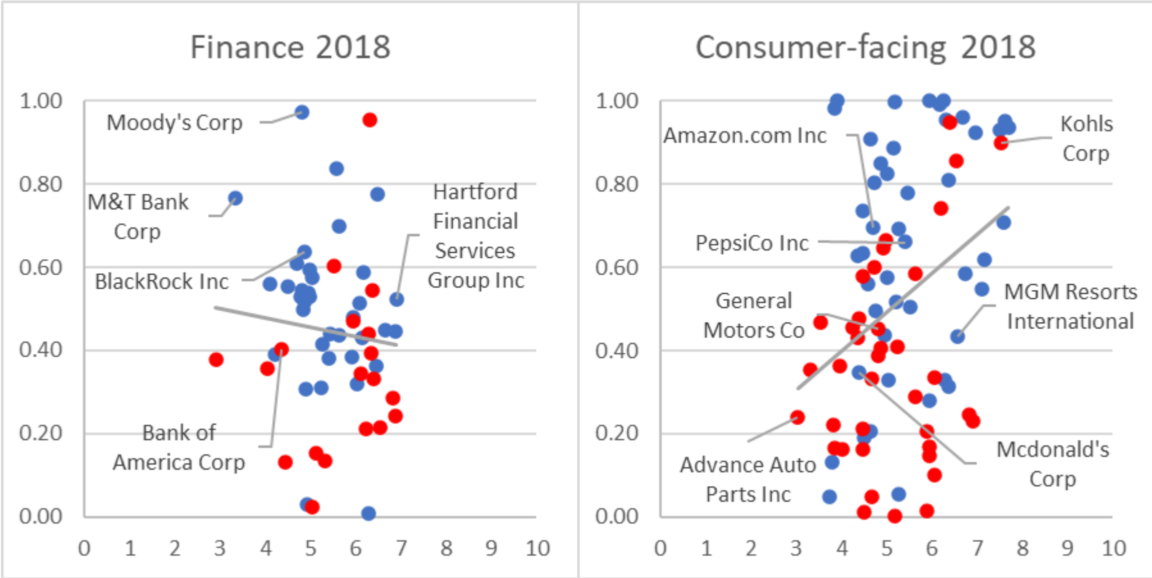

Figure 15: The continuous wokeness index vs share of donation

Both for healthcare and technology, the models are similar for the integer and the continuous wokeness index in terms intercept and slope. However, it seems that the integer model has slightly higher explanatory power with R-squared values of 9.11% and 8.93%, where the continuous models have R-squared values of 5.66% and 6.72%. Facebook has a score of 5 in the integer index, but only a score of 4.02 in the continuous index. Contrarily, HP scores 4 in the integer index and 4.85 in the continuous index. All highlighted companies in the healthcare graph and the remaining companies in the technology graph score similarly in both indices.

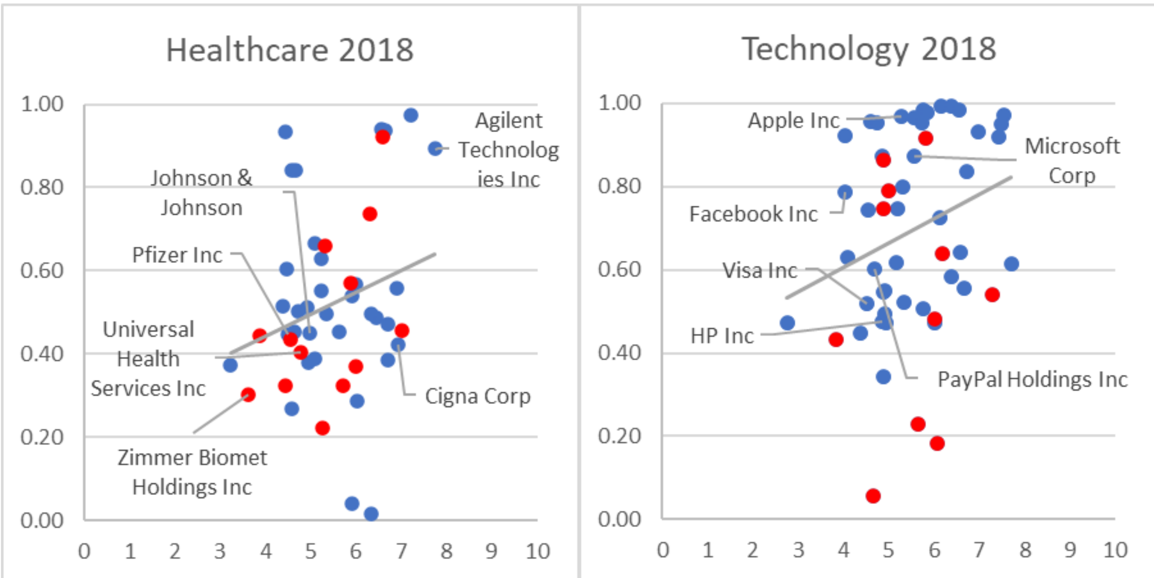

Figure 16: The continuous wokeness index vs share of donation

To see if the placement of a company's headquarter has an effect on the relationship between wokeness score and political donations, we plot trendlines for red and blue companies separately. Table 18 shows that blue companies tend to donate more to the Democrats, which is seen by either a steeper slope or a higher intercept.

	Red companies		*Blue companies*	
	Intercept	**Slope**	**Intercept**	**Slope**
Energy and utility	-0.2402	0.0928	-0.3861	0.1459
Industrial	0.1907	0.0393	-0.2118	0.1112
Finance	0.1572	0.0339	0.7793	-0.0522
Consumer-facing	0.0544	0.0621	0.2185	0.0775
Technology	0.5117	0.0042	0.3674	0.0666
Healthcare	-0.0557	0.0903	0.3597	0.0322
All industries	0.0764	0.0550	0.3124	0.0493

Table 18: Linear regression model for selected industries divided into the red and blue companies (2018 data)

Figure 17 shows the graph for all continuous wokeness scores vs the share of donations to Democrats for all industries combined. The graph clearly confirms the previous presumed pattern that blue companies tend to donate more to the Democrats while red companies donate mostly to Republicans. This is seen by the concentration of blue dots above the 50% donation mark and the concentration of red marks below the 50% donation mark. The trend for all industries indicates a slightly positive correlation, indicating that an increase of one in the wokeness score increases donations to the Democrats by 6.21%. The R-squared for the model is 5.39%, which indicates that the donations explain only 5.39% of the variation in the wokeness scores.

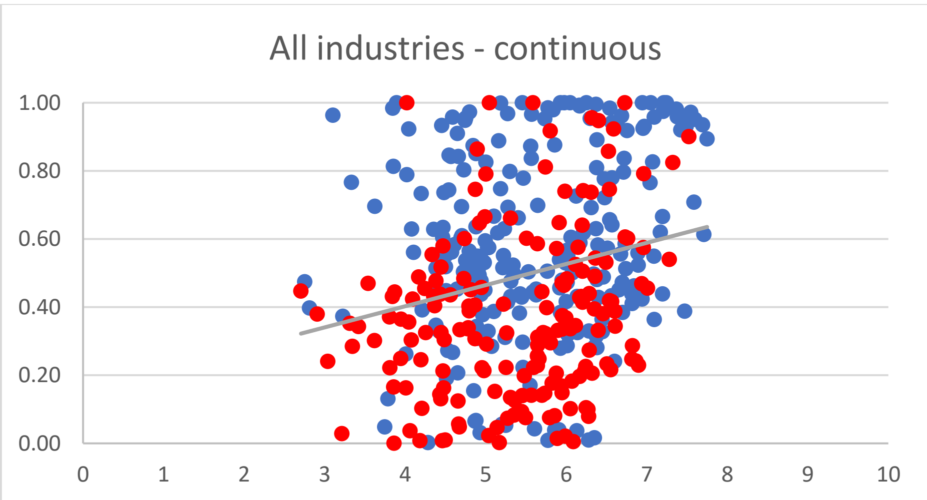

Figure 17: The continuous wokeness index vs share of donations to the Democrats for all industries

Since we use company donations in the wokeness index and as the dependent variable in the linear regressions there is a forced correlation in the graphs. The reference article avoids this correlation by using employee donations in their wokeness index and company donations as the dependent variable. To investigate how the correlation skews the result relative to the results of the reference article we exclude the political donation data from the wokeness index and run the linear regressions for the continuous model again.

5.2.1 Continuous wokeness graphs without political donation data

The results of the linear regressions are shown in Table 19. The results look similar to what we see in Table 17. The slopes are, in general, less steep, which is what we would expect when we remove some of the correlation. The R-squared values have decreased for all industries except for the finance industry. For industrials, consumer-facing, healthcare, and technology the R-squared values are less than 1% indicating no explanatory power. The R-squared for finance is equal to 12.12%, which is higher than in the two previous models. Indicating that taking out the donation score of the wokeness index increase the correlation between political donations and wokeness. The negative slope for finance indicates that an increase of one in wokeness score will decrease the donations to the Democrats by 7.05%. The corresponding graphs can be found in Appendix 2.

Industry	**R^2**	**Intercept**	**Slope**
Energy and Utilities	6.61%	-0.0429	0.0693
Industrials	0.97%	0.2973	0.0238
Finance	12.12%	0.7879	-0.0705
Consumer-facing	0.61%	0.4131	0.0225
Healthcare	0.04%	0.4994	0.0044
Technology	0.24%	0.6353	0.0116
All industries	0.13%	0.5457	-0.0099

Table 19: Linear regression for share of donation to the Democrats and wokeness index without political donation data in 2018

Figure 18 shows the continuous wokeness scores without political donation data. The graphs show the same tendencies as in Figure 17, where the majority of the blue companies are placed above the 50% donation mark and the majority of the red companies are placed below. Even when excluding the donation data the companies with the highest wokeness scores are blue. However, the slope indicates a negative correlation between wokeness and political donations. However, the model has close 0% explanatory power of the total data.

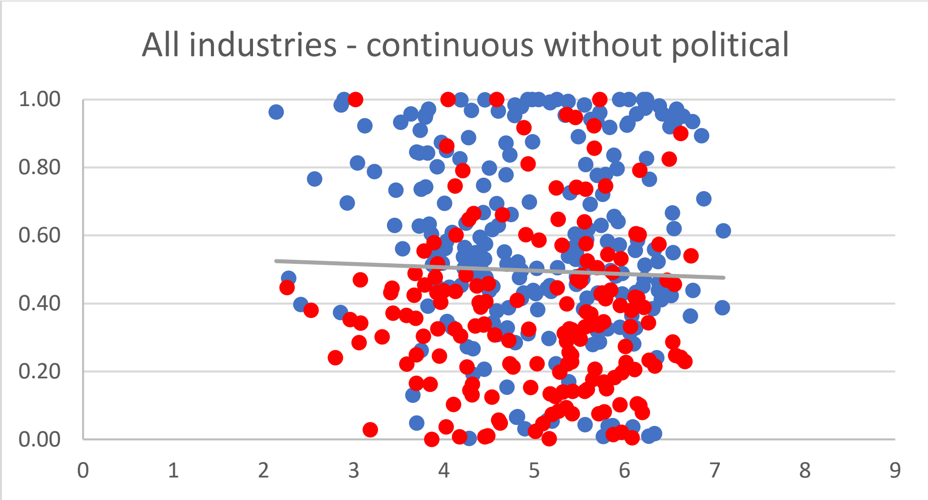

Figure 18: The continuous wokeness score without political donation data vs percentage-wise donations to the Democrats

Even without including the political data, we still see that in most industries an increase in wokeness leads to higher donations to the Democrats, indicating a correlation between wokeness and political donations. As we want to investigate the correlation between wokeness scores and financial performance we do not exclude the political donations data from our index. The integer and continuous indices yield quite similar wokeness scores with a few exceptions. We decide to use only the continuous index in further experiments as the scores are more precise. Furthermore, we cannot distinguish between companies with the same scores in the integer index making the construction of the wokeness portfolios difficult.

5.3 Consistency of the wokeness score through time

To investigate the consistency of the wokeness index through time, we create heatmaps that allow easy visualization. We want to analyze if the wokeness scores of companies are consistent throughout the selected period to see if the wokeness portfolios contain the same companies every year. The heatmaps are constructed based on three components of the wokeness index and the total wokeness score. Horizontally one rectangle indicates one company, and the vertical axis indicates the year. For the earlier years, we do not have observations for all companies due to missing data, hence some of the fields are white. The color scale is set up to be red for the lowest scores and dark green for the highest scores, fluently changing colors for everything in between. The heatmaps are sorted from low to high scores in 2018, each column indicates one company and its score through time.

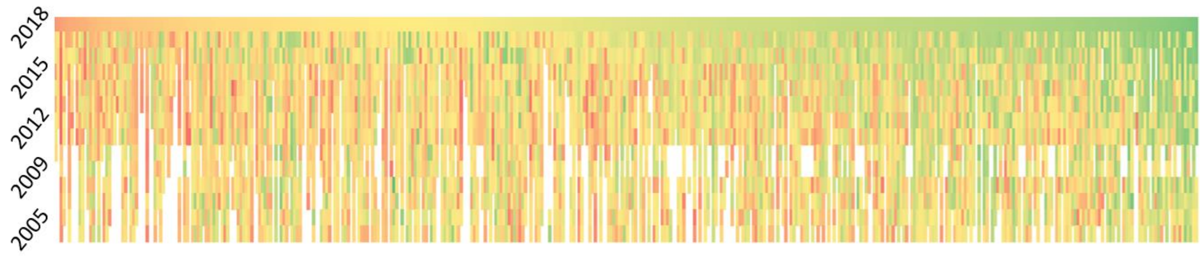

Figure 19: Heatmap showing the consistency of the total score assigned to companies in the 2005-2018, where 2005 is the bottom row and 2018 is the top row. Low scores are indicated by red colors changing towards green as the scores increase

The heatmap in Figure 19 shows the distribution of total wokeness scores through time sorted from low to high scores in 2018. The years are descending vertically from the top and the scores increasing horizontally from the left. The color pattern shows more green on the right side, but there are still yellow and red colors present, indicating that the companies in the top portfolios will differ each year. The dominating color on the left side is orange, however, there are also inconsistencies as indicated by the red, yellow, and green rectangles.

We would expect the individual company's score to improve over time or stay the same, meaning that the colors should go from darker red and orange colors to more yellow and green. However, the heatmap indicates is that there is little consistency in improvements.

Recall that Figure 1 showed a general increasing trend in the average ESG score, where the Controversies score (Figure 4) showed a less clear but slightly decreasing trend. This pattern could be the same on company level, hence we will examine the heatmaps for the three wokeness components separately. Figure 20, Figure 21, and Figure 22 show the heatmaps for the ESG score, the Controversies score, and the political donation score in the mentioned order.

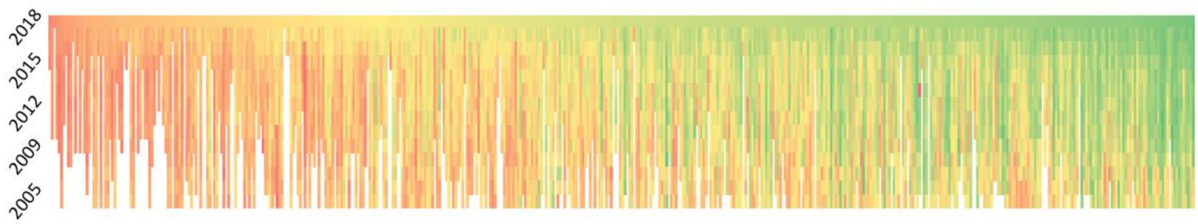

Figure 20: Heatmap showing the consistency of the ESG score assigned to companies in the 2005-2018, where 2005 is the bottom row and 2018 is the top row. Low scores are indicated by red colors changing towards green as the scores increase

The heatmap of the ESG scores in Figure 20 shows higher consistency in the colors. The color pattern indicates that companies generally improve their ESG scores over time. However, the companies with the lowest scores seem to have quite consistent scores over time.

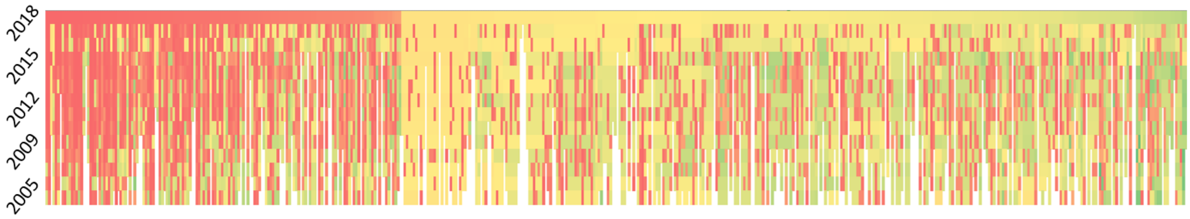

Figure 21: Heatmap showing the consistency of the Controversies score assigned to companies in the 2005-2018, where 2005 is the bottom row and 2018 is the top row. Low scores are indicated by red colors changing towards green as the scores increase

Figure 21 shows the heatmap for the Controversies score. There are more red colors on the left side of the heatmap, which indicate that companies that have had many controversies one year are more likely to have many controversies during the following years. The color patterns of the middle and right side are less consistent, indicating that most companies will have controversies from time to time. The scores also seem to be lower overall compared to the ESG score, as there are more red colors and little green.

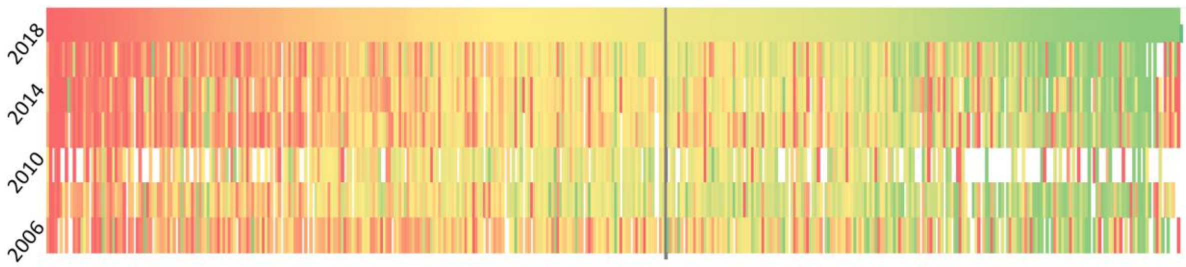

Figure 22: Heatmap showing the consistency of the political donation score assigned to companies in the 2006-2018 in two year intervals, where 2006 is the bottom row and 2018 is the top row.

Figure 22 shows the heatmap for political donations. The red color indicates low percentage donations to the Democrats, and the green colors indicate high percentage donations to the Democrats. The grey line is the 50% cutoff line for 2018 donations. The heatmap indicates that some companies are consistent in their political donations, while most companies' political donations vary from year to year. This pattern can be seen on both sides of the cutoff line.

From the analysis above it seems that the three categories individually show higher consistency through time, than the total score. However, it is not clear from the individual heatmaps if it is the same companies that are scoring high or low each year in the different categories. To investigate the link between the scores in the different categories we combine all heatmaps, and sort on the total score for 2018. The top heatmap is the total score, the second heatmap after the first grey line is the ESG score, the third is the Controversies score, and the last is the political donation score.

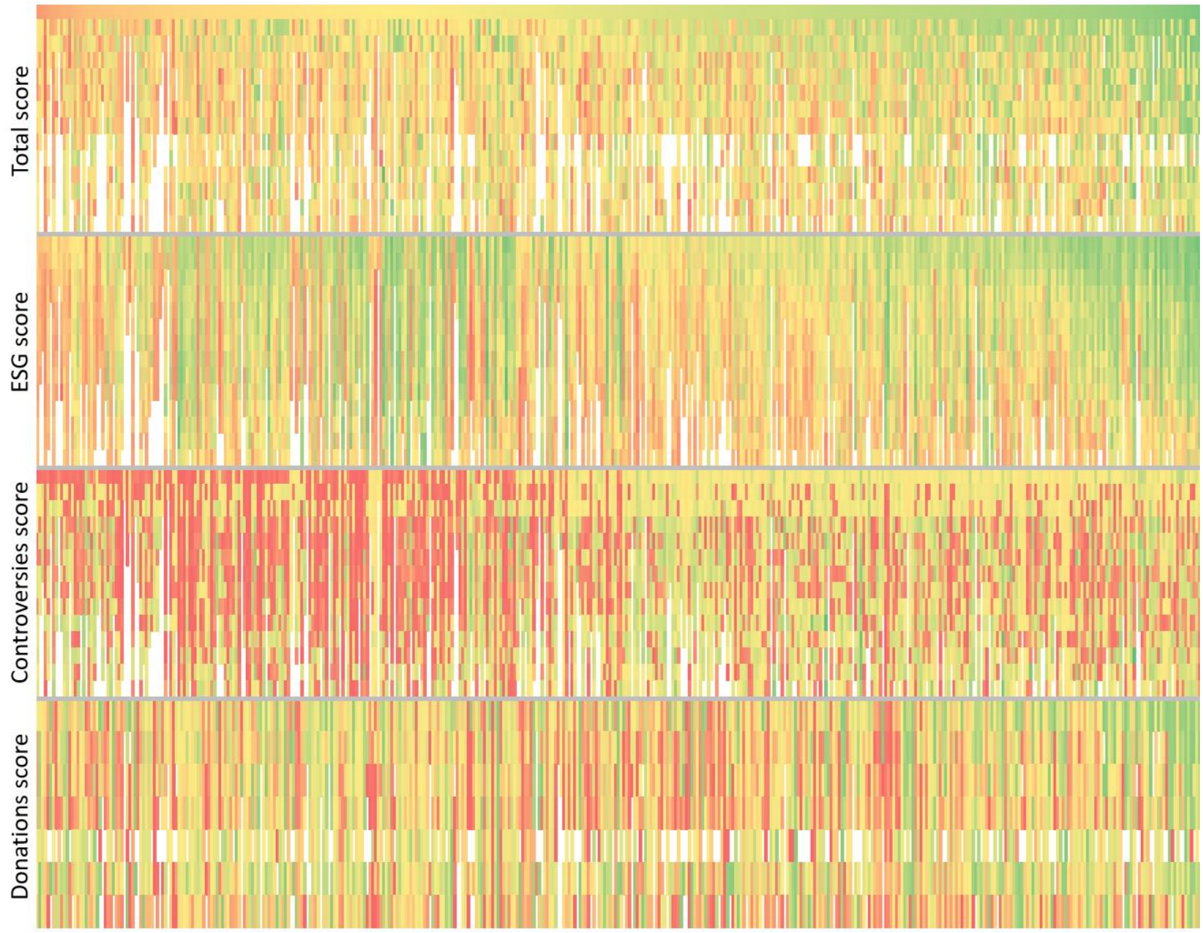

Figure 23: Heatmap showing total score and all three categories: ESG score, Controversies score, and political donation score. The heatmaps are sorted from low to high score in year 2018 from the total score

From the heatmap, in Figure 23 we see that most of the companies with a high total wokeness score also have a high ESG score. However, more companies with a lower total score also have high ESG scores, as we see many green columns on the left side of the ESG heatmap. These companies seem to have high Controversies scores, making the total score low. The low Controversies scores are mainly concentrated on the left side, but most companies have controversies from time to time, as there is red scatter across the rest of the plot. There is an overweight of green on the right side of the donation plot, and a slight overweight of red on the right side of the plot. In the middle of the plot there seem to be an overweight of companies with low ESG score, high Controversies score, and low donations score. To take a closer look at the distribution of the different scores in a specific year we plot heatmaps for 2018 and 2005. The heatmaps show the cutoff points for the different wokeness portfolios to illustrate what characteristics of the companies that are included in the portfolios.

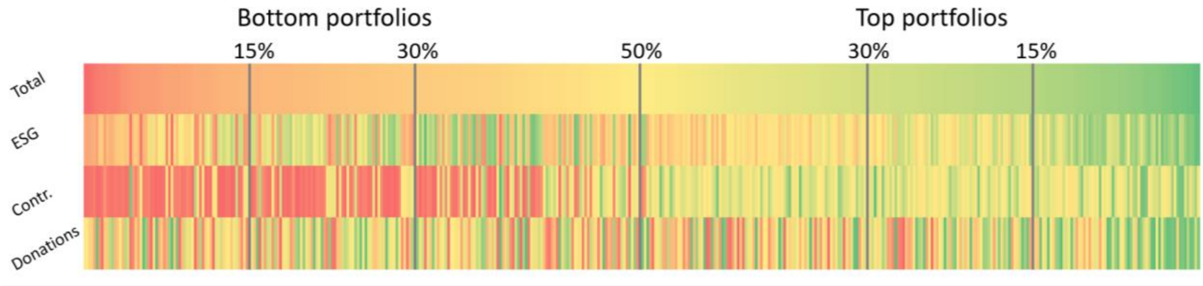

Figure 24: Heatmap of all four categories for the 2018 scores

Figure 24 indicates that the top 15 portfolio includes companies with high ESG scores, high Controversies score, and high donations score. However, there are a few companies with lower donation scores in this portfolio. The same pattern can be seen for the ESG and Controversies score in the top 30 portfolio, however, the portfolio includes more companies with low donation scores. The bottom 15 portfolio mainly includes companies with moderate to low ESG scores. Despite the low overall score, there are some companies with quite high ESG scores in the bottom 15 portfolio as there is some green visible in the portfolio. The controversies score seems to be very low for the majority of the companies in the bottom 15 portfolio. There seems to be a slight overweight of low donations scores in the bottom 15 portfolio, however, there are also few companies with high donations. In the bottom 30 portfolio, there are more companies with moderate to high ESG scores. However, these companies have very low controversies scores which are decreasing the total score. There is no clear trend in the donations score in the bottom 30 portfolio. The companies with the lowest ESG scores are manly places around the 50% mark, and these companies also seem to donate mostly to Republicans, as there are more red and orange colors present.

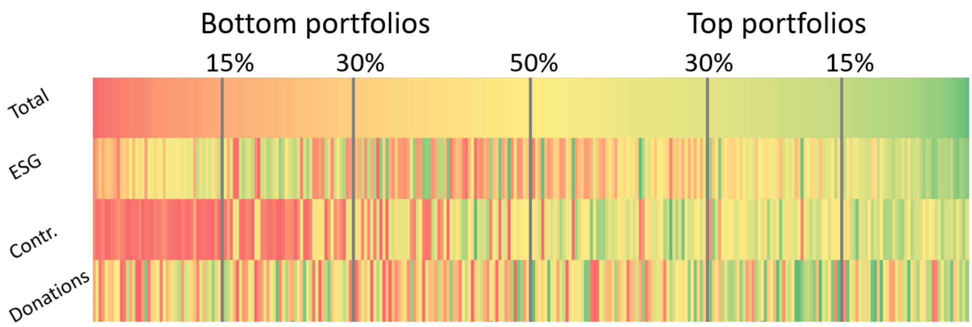

Figure 25: Heatmap of all four categories for the 2005 scores

The heatmap for the distribution of scores in 2005 (Figure 25) shows a similar distribution of the scores as the heatmap for 2018. The top 15 portfolio mainly includes companies with high ESG, controversies, and donations score, however, there are some companies with low donations scores included in this portfolio. The pattern for the top 30 portfolio shows a similar trend as the top 15 portfolio but the ESG and Controversies scores are generally lower. The bottom 15 and bottom 30 portfolios include the companies with the lowest Controversies score. The ESG scores in the bottom 15 and 30 portfolios are generally higher than the ESG scores of the companies placed around the 50% mark. The donations scores also tend to be lower around the 50% mark. The lowest-scoring companies in the bottom 15 portfolio have generally low donation scores; however, there are some companies with high donation scores in both the bottom 15 and bottom 30 portfolios.

As the distribution of scores in 2018 and 2005 are quite similar, we expect the distribution of scores in the remaining years to show a similar pattern.

5.4 Financial performance of the wokeness portfolios

To get a first impression of the financial performance of the wokest and least woke portfolios we plot the cumulative returns[3] for the different portfolios. The graphs below show the cumulative financial performance of all portfolio scenarios, where each portfolio is reevaluated every year so that the portfolios always include the current year's worst, neutral, and best performing-companies. The performance is graphed starting with a portfolio value of one and this value is then increasing (decreasing) with one plus the monthly average rate for the portfolio.

[3] $p_t = p_{t-1}(1 + r_{i,t})$, where p is the portfolio value and $r_{i,t}$ is the return for asset *i* at time t

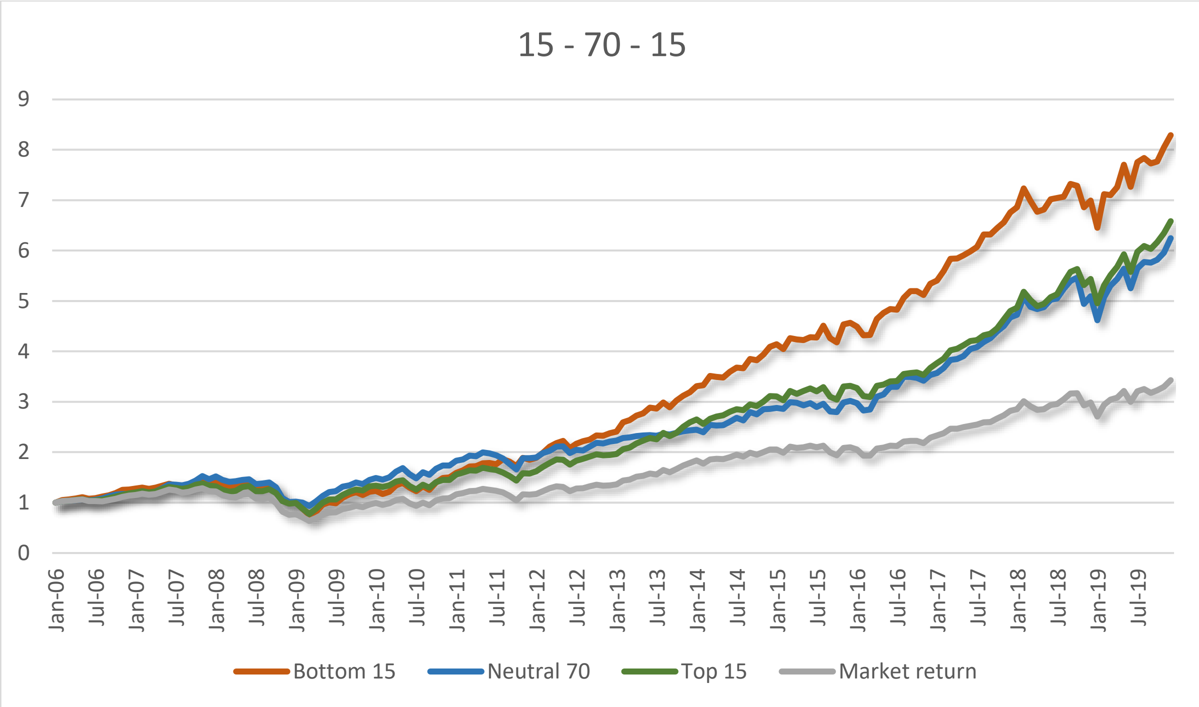

Figure 26: Cumulative returns for the bottom 15, neutral 70, and top 15 wokeness portfolios for the period 2006-2019

From Figure 26, which displays the cumulative returns for the bottom 15, neutral 70, and top 15 portfolios, we can see that during the period ranging from January 2006 to December 2019 the bottom 15 percent wokeness portfolio outperformed the other portfolios. The portfolios performed quite similarly at the beginning of the period until around late 2009 when the top portfolio slightly overperformed the bottom and the neutral portfolios. However, during early 2012 the bottom portfolio gained some momentum and started performing better than the two other portfolios. The top and neutral portfolios performed very similarly throughout the whole period until the very end of the sample period where the top portfolio performed somewhat better than the neutral portfolio, but the overall performance was still below the cumulative return of the bottom portfolio. All portfolios perform better than the market.

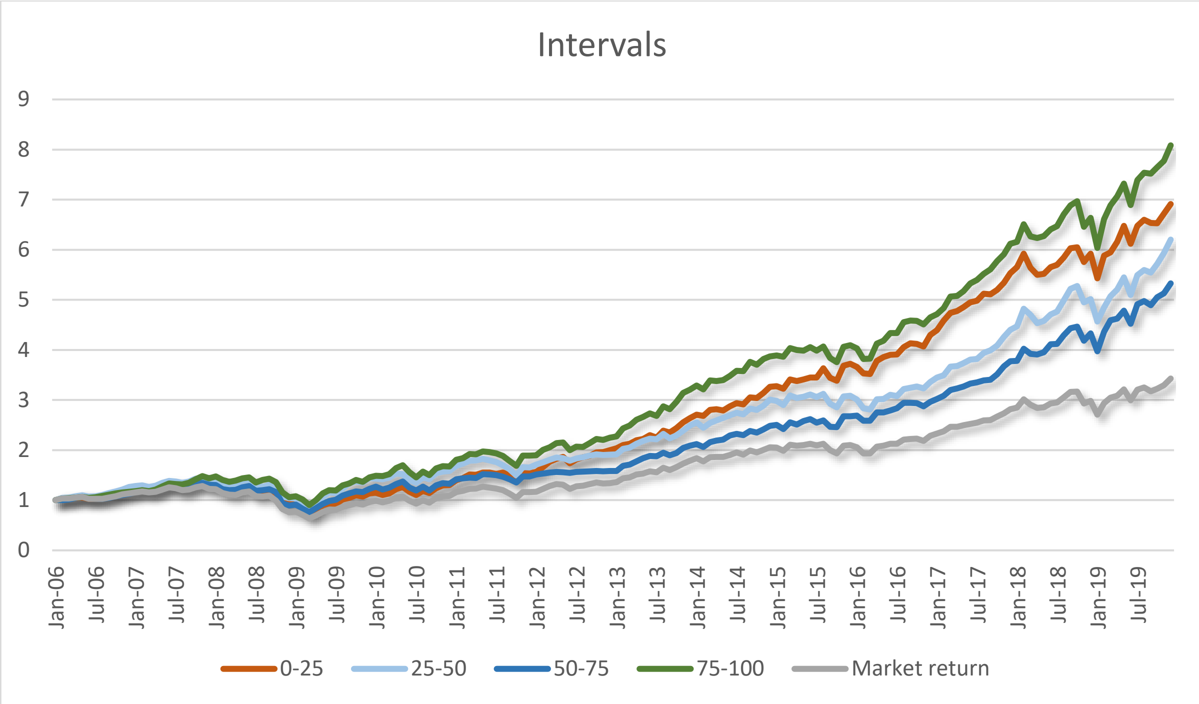

Figure 27: Cumulative returns for the bottom 25, neutral 25-50, neutral 50-75 and top 75-100 wokeness portfolios for the period 2006-2019.

The returns for the interval portfolios in Figure 27 show a different pattern than the bottom 15, neutral 70, and top 15 portfolios. All interval wokeness portfolios performed similarly until the financial crisis in late 2008. The 75-100 portfolio started to perform better than the other portfolios after the financial crisis. This trend continued throughout the remainder of the period. The portfolio with the second-highest cumulative returns was 0-25. The third best performing portfolio or the second-worst performing portfolio was the 25-50 wokeness portfolio and the worst performing portfolio was the 50-75 portfolio. All portfolios performed better than the market during this period.

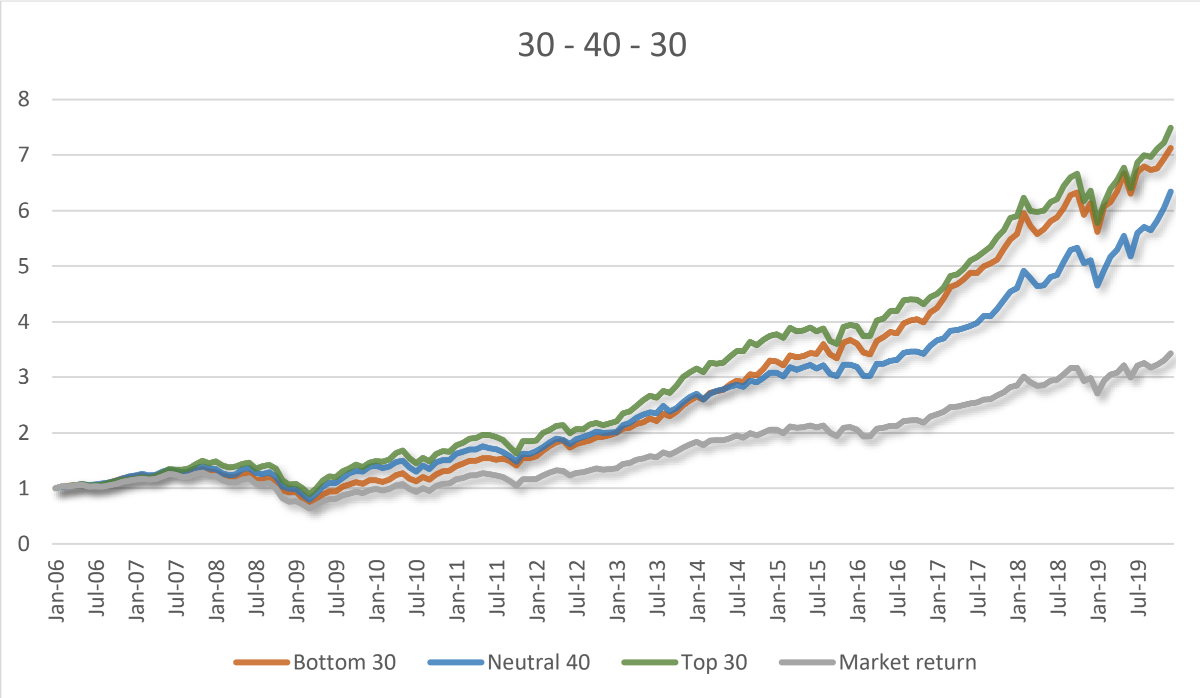

Figure 28: Cumulative returns for the bottom 30, neutral 40, and top 30 wokeness portfolios for the period 2006-2019

From Figure 28 we can see that that the bottom 30, neutral 40, and top 30 portfolios all performed similarly until the financial crisis. After the financial crisis, the top 30 portfolio and the neutral 40 portfolio performed marginally better than the bottom 30 portfolio. The top 30 portfolio outperformed the bottom 30 and the neutral 40 portfolios through the remainder of the period. The bottom 30 and neutral 40 portfolios showed a similar pattern in their cumulative returns until mid-2014 when the bottom 30 portfolio started performing better than the neutral 40 portfolio. During the stock market dip in late 2018, the cumulative returns of the top and bottom 30 portfolios were very similar. Both 30 portfolios outperformed the neutral 40 portfolio at the end, with the top 30 portfolio ending up with the highest cumulative return. All portfolios performed better than the market during this period.

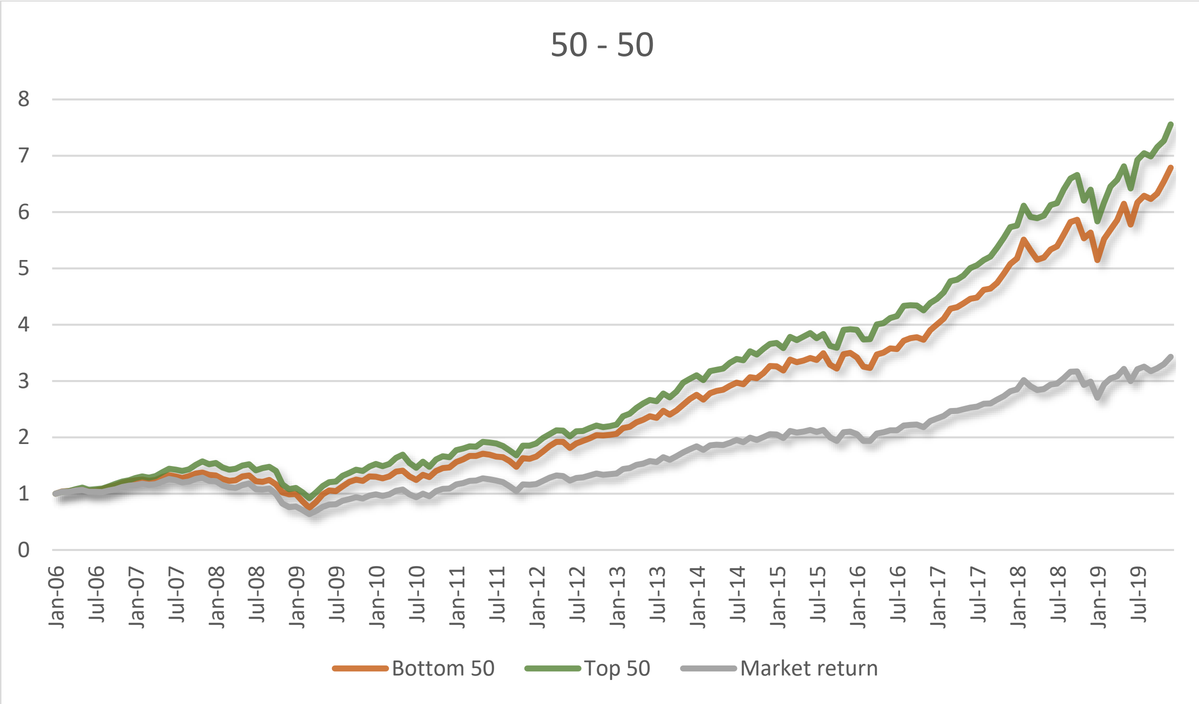

Figure 29: Cumulative returns for the bottom 50 and top 50 wokeness portfolios for the period 2006-2019.

The cumulative returns of the top 50 and bottom 50 portfolios were not that different from what we can see in Figure 27 and Figure 28. The top 50 portfolio outperformed the bottom 50 portfolio during the whole period. The difference between the best and the worst performing portfolio is narrower in the top and bottom 50 portfolios compared to the other portfolio scenarios.

Overall we can see that the cumulative return was highest for the bottom 15 portfolio. The worst performing portfolio of all portfolios was the 50-75 interval portfolio. We can only see the bottom portfolio outperform the top portfolio in the first portfolio scenario. When comparing all portfolios which contained the companies with the highest woke scores with each other, we can see that the top 30 portfolio had the highest cumulative returns compared to the other top portfolios. When comparing the worst scoring portfolios with each other the bottom 50 portfolio has the lowest cumulative returns. When looking at the difference between the highest and the lowest cumulative returns within each set of portfolios, the difference between the best and the worst performing portfolios is the widest interval portfolios. All portfolios performed better than the market during this period.

5.5 Regression results

The graphs for the cumulative financial returns indicate how each of the portfolios developed over time, but we cannot use these results to see if the returns are significantly different from each other. To estimate the performance of the portfolios we will in this section apply factor models.

5.5.1 Fama and French 3-factor model

5.5.1.1 Value weighted portfolios

Table 20 shows the results for the regression using the Fama and French 3-factor model. Examining scenario one, we see that the excess return of the bottom 15 portfolio is 0.6%, which is 0.1% higher than for the top 15 and 0.2% higher than for the neutral 70 portfolio. All alphas are significantly different from 0 with p-values below 0.001. However, all confidence intervals overlap and the standard error of bottom 15 is higher than for the other two portfolios, which makes the confidence intervals wider.

To ensure that the model is performing well we investigate the factors. Betas for all three portfolios are significantly different from 0 with p-values below 0.001. The betas are relatively close to 1, and 1 is included in the confidence intervals for all three portfolios. The 95%-confidence interval means that we are 95% certain that the true value is included in the interval. In other words, we cannot reject that beta is 1 for any of the portfolios.

The SMB factor captures the fact that small companies have outperformed the big companies in the past. The coefficients for SMB are all negative and relatively close to 0 for the top 15 and bottom 15. The p-values for top 15 and bottom 15 show that the coefficients are insignificant, meaning that we cannot reject that they are different from 0. The p-value for neutral 70 is below 0.001, indicating that the probability of the coefficient being different from 0 is 99.9%.

The HML factor captures the fact that historically value stocks have outperformed growth stocks. The coefficient for HML top 15 is slightly negative, where the neutral 70 and bottom 15 are slightly positive. They are all significantly different from 0 with p-values equal to or below 0.001.

Value weighted wokeness portfolio: Fama and French 3-factor model

$$r_i - r_f = \alpha_i + b_i \mathrm{MktRF} + s_i SMB + h_i HML + \epsilon_i$$

	Bottom 15	Neutral 70	Top 15	0-25	25-50	50-75	75-100	Bottom 30	Neutral 40	Top 30	Bottom 50	Top 50
a_i	0.006	0.0043	0.0051	0.005	0.004	0.0033	0.0055	0.0049	0.0042	0.0051	0.0046	0.0052
P-value	0	0	0	0	0.002	0.001	0	0	0	0	0	0
Std. Dev.	0.0013	0.0006	0.001	0.0009	0.0013	0.0009	0.0008	0.0009	0.0008	0.0009	0.0008	0.0007
CI lb	0.004	0.003	0.003	0.003	0.002	0.002	0.004	0.003	0.003	0.003	0.003	0.004
CI ub	0.009	0.006	0.007	0.007	0.006	0.005	0.007	0.007	0.006	0.007	0.006	0.006
b_i	0.9577	0.9764	0.9603	0.9181	1.0094	0.9149	0.9616	0.9607	0.9711	0.966	0.98	0.9516
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0324	0.0163	0.0254	0.0234	0.0324	0.0243	0.0215	0.023	0.0194	0.0219	0.0212	0.0171
CI lb	0.894	0.944	0.91	0.872	0.945	0.867	0.919	0.915	0.933	0.923	0.938	0.918
CI ub	1.022	1.009	1.01	0.964	1.073	0.963	1.004	1.006	1.009	1.009	1.022	0.985
s_i	-0.0723	-0.2155	-0.0125	-0.1311	-0.2842	-0.1237	-0.0423	-0.1974	-0.2096	-0.0577	-0.2281	-0.0964
P-value	0.213	0	0.784	0.002	0	0.005	0.272	0	0	0.143	0	0.002
Std. Dev.	0.0578	0.0291	0.0454	0.0418	0.058	0.0434	0.0384	0.0411	0.0347	0.0392	0.0378	0.0306
CI lb	-0.186	-0.273	-0.102	-0.214	-0.399	-0.209	-0.118	-0.278	-0.278	-0.135	-0.303	-0.157
CI ub	0.042	-0.158	0.077	-0.049	-0.17	-0.038	0.034	-0.116	-0.141	0.02	-0.153	-0.036
h_i	0.1683	0.1138	-0.1247	0.1334	0.148	0.0441	0.0453	0.108	0.1086	0.058	0.1436	0.0485
P-value	0.001	0	0.001	0	0.003	0.227	0.162	0.002	0	0.08	0	0.061
Std. Dev.	0.0485	0.0244	0.0381	0.0351	0.0487	0.0364	0.0322	0.0345	0.0291	0.0329	0.0317	0.0257
CI lb	0.072	0.066	-0.2	0.064	0.052	-0.028	-0.018	0.04	0.051	-0.007	0.081	-0.002
CI ub	0.264	0.162	-0.05	0.203	0.244	0.116	0.109	0.176	0.166	0.123	0.206	0.099
Adj. R^2	0.8675	0.9617	0.908	0.9176	0.8706	0.9084	0.9350	0.9245	0.9459	0.9331	0.9380	0.9560

Table 20: Fama and French 3-factor regression results of the four different scenarios. The portfolios are sorted yearly based on the end-year wokeness scores (2005-2018) and the value weighted monthly returns from the beginning of the year (2006-2019).

The model's total explanatory power is captured in the adjusted R-squared, which is relatively high for all the portfolios. Top 15 has an adjusted R-squared value equal to 0.908 meaning that 90.8% of the variation in the portfolios' returns is explained by the 3 factors. The adjusted R-squared is highest for neutral 70 and lowest for the bottom 15.

Looking at scenario 2, we see a slightly different picture as the alpha is highest for the wokest companies in 75-100, closely followed by the least woke companies in 0-25. All four alphas are significantly different from 0 indicating that they all outperform the market. However, the confidence intervals are all overlapping, suggesting that we cannot be certain that they are different from each other. We cannot reject that beta is 1 for 25-50 and 75-100. For the two other portfolios, beta is relatively close to 1 but not included in the 95%-confidence intervals. For the SMB and HML, five of the coefficients are significantly different from 0 with p-values below 5%. The adjusted R-squared values for all portfolios are relatively high, 87.06% for 25-50, and above 90% for the other portfolios.

In scenario 3, the wokest companies in the top 30 perform best with an alpha of 0.51%, closely followed by the bottom 30 that has an alpha of 0.49%. Alphas for all three portfolios are significantly different from 0 with p-values below 0.001. However, we still see that the confidence intervals are overlapping. Looking at the betas we see that 1 is included in the confidence intervals for all three portfolios. For the two factors SMB and HML the coefficients are all significantly different from 0 with p-values below 0.05, except SMB for top 30 that has a p-value of 0.143. The model seem to explain the variation in data well as all three portfolios have an adjusted R-squared above 92%

In the last scenario, alpha is still the highest for the top portfolio. The top 50 alpha is 0.52%, where the bottom 50 alpha is 0.46%, and they are both significantly different from 0. However, we still see an overlap in the 95%-confidence intervals. The betas are both close to 1 but only the bottom 50 has 1 included in the 95%-confidence interval. The coefficients for SMB are both negative and significantly different from 0 with p-values below 0.01. The HML coefficient for the top 50 has a p-value of 0.061, which is close to our chosen significance level. The bottom 50 is significantly different from 0 with a p-value below 0.001. The overall explanatory power of the model is good, with adjusted R-squared values above 93% for both portfolios.

Comparing the different scenarios we see that the first scenario is different from the others, as the bottom portfolio has the highest excess return. However, the top and bottom 15 have a lower adjusted R-squared, indicating that less of the variation in the returns is explained by the model. The model explains the bottom and top portfolios well in the second scenario as they have higher adjusted R-squared values, but the neutral portfolios have slightly lower adjusted R-squared.

When using the value-weighted portfolios, we suspect that a few big companies are driving the returns, especially in the small portfolios, hence we test the sensitivity of all scenarios by equally weighting the returns.

5.5.1.2 Equally weighted portfolios

Table 21 shows the regression results for the equally weighted portfolios using the Fama and French 3-factor model. Looking at the alphas we see the same patterns in the two first scenarios as for the value weighted portfolios. The highest alphas are the bottom 15 and 75-100, and the lowest alphas are for the neutral 70 and 50-75. In the third and fourth scenarios, the alphas for the equally weighted portfolios are the opposite of what we see in the value-weighted portfolios. Alpha is highest for the bottom 30 and bottom 50 portfolios, and lowest for neutral 40 and top 50. All alphas are significantly different from 0 with p-values below 0.05. All betas for the market factor are significantly different from 0. All of the betas are close to 1. The coefficients for SMB are in general closer to 0, but for the equally weighted portfolios, they are all positive. This indicates a substantially different influence of the size factor. Eight out of twelve of the coefficients are significantly different from 0 with p-values below 0.05. The coefficients for HML are still all positive except for the top 15 coefficient. The coefficients for HML are in general higher in the equally weighted portfolios compared to the value-weighted portfolios. All HML coefficients, except 75-100, are significant with p-values below 5%. The lowest adjusted R-squared values are on average slightly higher for the equally weighted portfolios.

Equal weighted wokeness portfolio: Fama and French 3-factor model

$$r_i - r_f = \alpha_i + b_i \text{MktRF} + s_i SMB + h_i HML + \epsilon_i$$

	Bottom 15	Neutral 70	Top 15	0-25	25-50	50-75	75-100	Bottom 30	Neutral 40	Top 30	Bottom 50	Top 50
a_i	0.0033	0.0025	0.0028	0.0029	0.0026	0.0021	0.0032	0.0031	0.002	0.0026	0.0026	0.0024
P-value	0.013	0.001	0.002	0.008	0.005	0.019	0	0.004	0.023	0.001	0.006	0.002
Std. Dev.	0.0013	0.0007	0.0009	0.0011	0.0009	0.0009	0.0007	0.0011	0.0009	0.0008	0.0009	0.0008
CI lb	0.001	0.001	0.001	0.001	0.001	0	0.002	0.001	0	0.001	0.001	0.001
CI ub	0.006	0.004	0.005	0.005	0.004	0.004	0.005	0.005	0.004	0.004	0.004	0.004
b_i	1.1015	1.0384	0.9894	1.0762	1.0519	1.0272	1.0013	1.0508	1.0386	0.989	1.0545	1.0011
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0337	0.0186	0.0224	0.0281	0.0237	0.0226	0.0191	0.0272	0.022	0.0202	0.0238	0.0196
CI lb	1.035	1.002	0.945	1.021	1.005	0.983	0.964	0.997	0.995	0.949	1.008	0.963
CI ub	1.168	1.075	1.034	1.132	1.099	1.072	1.039	1.105	1.082	1.029	1.101	1.04
s_i	0.1392	0.0853	0.058	0.1154	0.0405	0.1194	0.0812	0.0991	0.0588	0.0841	0.0665	0.0892
P-value	0.022	0.011	0.149	0.023	0.341	0.004	0.019	0.043	0.137	0.021	0.119	0.012
Std. Dev.	0.0602	0.0333	0.04	0.0503	0.0424	0.0405	0.0342	0.0486	0.0393	0.0362	0.0425	0.035
CI lb	0.02	0.02	-0.021	0.016	-0.043	0.04	0.014	0.003	-0.019	0.013	-0.017	0.02
CI ub	0.258	0.151	0.137	0.215	0.124	0.199	0.149	0.195	0.136	0.155	0.15	0.158
h_i	0.1816	0.1943	-0.0762	0.1881	0.2308	0.1533	0.0382	0.1929	0.2088	0.0647	0.2169	0.1046
P-value	0	0	0.025	0	0	0	0.185	0	0	0.034	0	0.001
Std. Dev.	0.0505	0.0279	0.0336	0.0422	0.0356	0.034	0.0287	0.0408	0.033	0.0303	0.0356	0.0294
CI lb	0.082	0.139	-0.142	0.105	0.161	0.086	-0.018	0.112	0.144	0.005	0.146	0.047
CI ub	0.281	0.249	-0.01	0.271	0.301	0.22	0.095	0.273	0.274	0.125	0.287	0.163
Adj. R^2	0.8958	0.9613	0.9337	0.9215	0.9399	0.9425	0.9538	0.9228	0.9466	0.9479	0.9402	0.9528

Table 21: Fama and French 3-factor regression results of the four different scenarios. The portfolios are sorted yearly based on the end-year wokeness scores (2005-2018) and the equal weighted monthly returns from the beginning of the year (2006-2019).

In general, the alphas are higher in the value-weighted portfolios, indicating that bigger companies might be driving the abnormal return. The adjusted R-squared values are slightly higher for the equally weighted portfolios, indicating that the models explain more of the variation in the returns when the portfolios are equally weighted compared to when they are value-weighted. It seems that the more of the HML coefficients are significant for the equally weighted portfolios than for the value-weighted portfolios.

Carhart 4-factor model

To test the sensitivity of our results and to see if adding one more factor yields a more precise estimate we test the Carhart 4-factor model. Hendricks, Patel, and Zeckhauser (1993) and Jegadeesh and Titman (1993) suggest a persistent short term outperformance of mutual funds that hold a “hot hand” or momentum stocks, which the Carhart 4-factor model adjusts for. However, as we are not investigating the performance of mutual funds, but wokeness portfolios this model might not be giving us the most correct alphas. One could argue that the portfolios we are constructing are behaving similar to a mutual fund, but we are not actively seeking the best-performing companies, hence this model might not be the best to capture the true alpha.

5.5.1.3 Value weighted portfolios

Table 22 presents the estimated coefficients for the Carhart 4-factor model. Examining the results of scenario one, we see that the alpha is highest for the bottom 15 portfolio while it is the lowest for the neutral 70 portfolio. The alphas are 0.60% and 0.44%, respectively. The p-values are all under 0.001 indicating that all alphas are significantly different from 0. The standard error for the bottom 15 portfolio is the highest meaning that the confidence interval for the portfolio is the widest. The 95%-confidence intervals for all alphas are overlapping meaning we cannot be sure that the alphas are different from one another.

The betas for all portfolios are significantly different from 0 with p-values under 0.001. The betas are all under but relatively close to 1, and 1 is included in the confidence intervals for the bottom 15 and top 15 portfolios, but not the neutral 70 portfolio.

Value weighted wokeness portfolio: Carhart 4-factor model

$$r_i - r_f = \alpha_i + b_i \mathrm{MktRF} + s_i SMB + h_i HML + m_i MOM + \epsilon_i$$

	Bottom 15	**Neutral 70**	**Top 15**	**0-25**	**25-50**	**50-75**	**75-100**	**Bottom 30**	**Neutral 40**	**Top 30**	**Bottom 50**	**Top 50**
a_i	0.0060	0.0044	0.0051	0.0050	0.0041	0.0033	0.0056	0.0049	0.0042	0.0051	0.0046	0.0052
P-value	0	0	0	0	0.001	0.001	0	0	0	0	0	0
Std. Dev.	0.0013	0.0006	0.0010	0.0009	0.0012	0.0010	0.0008	0.0009	0.0008	0.0008	0.0008	0.0007
CI lb	0.004	0.003	0.003	0.003	0.002	0.001	0.004	0.003	0.003	0.003	0.003	0.004
CI ub	0.009	0.006	0.007	0.007	0.006	0.005	0.007	0.007	0.006	0.007	0.006	0.006
b_i	0.9468	0.9642	0.9572	0.9123	0.9854	0.9169	0.9516	0.9513	0.9648	0.9516	0.9625	0.9522
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0336	0.0166	0.0264	0.0243	0.0331	0.0253	0.0222	0.0238	0.0201	0.0225	0.0215	0.0179
CI lb	0.880	0.931	0.905	0.864	0.920	0.867	0.908	0.904	0.925	0.907	0.920	0.917
CI ub	1.013	0.997	1.009	0.960	1.051	0.967	0.996	0.998	1.005	0.996	1.005	0.987
s_i	-0.0713	-0.2144	-0.0122	-0.1306	-0.2819	-0.1239	-0.0414	-0.1965	-0.2090	-0.0563	-0.2265	-0.0964
P-value	0.219	0	0.789	0.002	0	0.005	0.281	0	0	0.147	0	0.002
Std. Dev.	0.0578	0.0286	0.0455	0.0418	0.0569	0.0435	0.0382	0.0409	0.0346	0.0387	0.0369	0.0307
CI lb	-0.185	-0.271	-0.102	-0.213	-0.394	-0.210	-0.117	-0.277	-0.277	-0.133	-0.299	-0.157
CI ub	0.043	-0.158	0.078	-0.048	-0.169	-0.038	0.034	-0.116	-0.141	0.020	-0.154	-0.036
h_i	0.1427	0.0850	-0.1319	0.1197	0.0915	0.0487	0.0217	0.0858	0.0939	0.0241	0.1022	0.0499
P-value	0.008	0.001	0.002	0.002	0.082	0.224	0.536	0.024	0.004	0.498	0.003	0.079
Std. Dev.	0.0530	0.0262	0.0418	0.0384	0.0523	0.0399	0.0351	0.0376	0.0318	0.0355	0.0339	0.0282
CI lb	0.038	0.033	-0.214	0.044	-0.012	-0.030	-0.048	0.012	0.031	-0.046	0.035	-0.006
CI ub	0.247	0.137	-0.049	0.196	0.195	0.128	0.091	0.160	0.157	0.094	0.169	0.106
m_i	-0.0379	-0.0426	-0.0106	-0.0202	-0.0835	0.0068	-0.0348	-0.0329	-0.0218	-0.0501	-0.0612	0.0021
P-value	0.234	0.007	0.671	0.381	0.008	0.775	0.099	0.146	0.254	0.020	0.003	0.903
Std. Dev.	0.0317	0.0157	0.0250	0.0230	0.0313	0.0239	0.0210	0.0225	0.0190	0.0212	0.0203	0.0169
CI lb	-0.101	-0.074	-0.060	-0.066	-0.145	-0.040	-0.076	-0.077	-0.059	-0.092	-0.101	-0.031
CI ub	0.025	-0.012	0.039	0.025	-0.022	0.054	0.007	0.012	0.016	-0.008	-0.021	0.035
Adj. R^2	0.8678	0.9632	0.9076	0.9175	0.8753	0.9079	0.9357	0.9259	0.9460	0.9349	0.9409	0.958

Table 22: Carhart 4-factor regression results of the four different scenarios. The portfolios are sorted yearly based on the end-year wokeness scores (2005-2018) and the value weighted monthly returns from the beginning of the year (2006-2019).

The SMB factor is negative for all portfolios, however, the p-value is only significant for the neutral 70 portfolio. This means that we cannot be sure that the factor coefficients for the bottom 15 and the top 15 portfolios are different from 0. The HML factor is slightly negative for the top 15 portfolio but positive for the other two portfolios. All p-values are significant. The MOM coefficient is negative but relatively close to 0 for all three portfolios but the p-value shows that the coefficient is only significant for the neutral 70 portfolio. The adjusted R-squared is highest for the neutral 70 portfolio at 0.9632 meaning that the model explains 96.32% of the variation in the returns.

The results of the second scenario reveal that the alpha is highest for the 75-100 portfolio. The alpha for the 75-100 portfolio is 0.56% above the market return. This result is different than the result in scenario one where it was the bottom portfolio which had the highest alpha. The second highest alpha in the second scenario is the 0-25 portfolio where the alpha is 0.06% lower compared to the highest alpha. The third highest alpha is for the 25-50 portfolio which was 0.15% lower than the highest alpha. The lowest alpha of 0.33% can be seen in the 50-75 portfolio which is 0.23% lower than the alpha of the 75-100 portfolio. We can see that there is some overlapping in the 95%-confidence intervals of the portfolios meaning we cannot be sure that the alphas differ from each other. The p-values for all alphas are below 0.01 indicating that they are significantly different from 0.

The betas in the second scenario are all under but quite close to 1, 1 is only included in the 95%-confidence interval for the 25-50 portfolio which means we can be 95% sure that the betas for the other three portfolios are under one. All betas are significantly different from 0.

Looking at the SMB factor coefficients we see that the coefficients are all negative. The SMB coefficients are all significant with p-values below 0.01, except the 75-100 portfolio which has a p-value of 0.281. The HML coefficients are positive with p-values under 0.05 for all portfolios, except the 25-50 portfolio which has a p-value of 0.0523. The MOM coefficient is slightly negative for all portfolios except the 75-100 portfolio. The p-values are all significant under 0.05 indicating that the MOM coefficients are all different from 0. The adjusted R-squared is higher than 90% for all portfolios except for the 25-50 portfolio.

Looking at the third scenario we see that the alpha is highest for the top 30 portfolio where the alpha is 0.51% over the market return. The second highest alpha is in the bottom 30 portfolio where the alpha is 0.02% lower than in the top 30 portfolio. The neutral 40 portfolio has the lowest alpha at 0.42% which is 0.09% lower than the highest alpha. The highest alpha in scenario three is lower than the highest alphas of scenarios 1 and 2. All alphas have a p-value of under 0.001 indicating that the alphas are all significantly different from 0. Similar to the other scenarios, the 95%-confidence intervals are overlapping for all alphas meaning we cannot be sure that they are different from one another.

Looking at the betas we see that for all portfolios, the betas are under but relatively close to one. One is only included in the 95%-confidence interval for the neutral 40 portfolio meaning we can be 95% sure that the betas for the bottom 30 and top 30 portfolios are under 1. All betas are significant with p-values below 0.01.

The SMB coefficients are all negative and significant with p-values under 0.05 except the p-value for the top 30 portfolio which is 0.147. The HML coefficients are all positive and significant for the bottom and neutral portfolios. The MOM coefficient is negative for all portfolios, however, the p-value is only significant on a 5%-level for the top 30 portfolio. The adjusted R-squared values are all over 93% for this scenario.

The fourth and last scenario shows that the highest alpha of 0.52% is in the top 50 portfolio while alpha in the bottom portfolio is 0.46%. The p-values for both the bottom and top portfolios are under 0.001 indicating that the alphas are different from 0. Similarly to the other scenarios, there is overlapping in the 95%-confidence intervals of the alphas.

The betas are both under but close to 0 with p-values under 0.001. 1 is included in the 95%-confidence interval for the bottom 50 portfolio but not for the top 50 portfolio. The SMB coefficients are both negative and both have a p-value under 0.05. The HML coefficients are positive for both portfolios but the p-value for the top 50 portfolio is above 0.05. The MOM coefficient is slightly positive for the top 50 portfolio and slightly negative for the bottom 50 portfolio. Both MOM coefficients are significant on a 5%-level. The adjusted R-squared is highest for the top 50 portfolio.

5.5.1.4 Equally weighted results

Table 23 shows the results for the equally weighted portfolio using the Carhart 4-factor model. All portfolios exhibit a positive alpha and are significantly different from 0. All alphas are lower in the equally weighted portfolios, suggesting that the alphas in the value-weighted portfolios are generated by the biggest companies. The 95%-confidence intervals for all alphas in the equally weighted portfolios are overlapping meaning we cannot be sure that the alphas differ from one another.

For the first scenario, we see that the alphas follow the same patterns as they did in the value-weighted portfolio. The highest alpha of 0.36% is in the bottom 15 portfolio. The neutral 70 portfolio has the lowest alpha. All alphas are significant with p-values under 0.01. For the second scenario, the alphas follow the same pattern as in the value-weighted portfolio. The highest alpha is 0.33%. In the third scenario which includes the bottom 30, neutral 40, and top 30 portfolios we observe a different pattern for the portfolio alphas. The bottom 30 has an alpha of 0.33% which is the highest alpha for all three portfolios. In scenario four which includes the equally weighted bottom and top 50 portfolios, the results show that the bottom 50 portfolio has a higher alpha than the top 50 portfolio. This is different from what we see in the value-weighted portfolios.

The betas for all portfolios are relatively close to 1. All betas are significantly different from 0. 1 is included in all 95%-confidence intervals. Contrary to the value-weighted portfolios, the SMB coefficients are positive for all portfolios. The majority of the factors are significant as 8 out of 12 have P-values under 0.05. The HML coefficients are all positive except for the top 15 and 75-100 portfolios. However, the HML coefficient for 75-100 is not significantly different from 0 as the p-value is 0.44. The majority of the remaining p-values are below 0.05. The MOM factors all negative and significant. The adjusted R-squared values are all high, ranging from 92% to 97%.

Equal weighted wokeness portfolio: Carhart 4-factor model

$$r_i - r_f = \alpha_i + b_i \mathrm{MktRF} + s_i SMB + h_i HML + m_i MOM + \epsilon_i$$

	Bottom 15	Neutral 70	Top 15	0-25	25-50	50-75	75-100	Bottom 30	Neutral 40	Top 30	Bottom 50	Top 50
a_i	0.0036	0.0027	0.0029	0.0032	0.0028	0.0022	0.0033	0.0033	0.0021	0.0027	0.0028	0.0025
P-value	0.002	0	0.001	0.001	0.001	0.007	0	0.001	0.009	0.001	0.001	0.001
Std. Dev.	0.0011	0.0006	0.0009	0.0009	0.0008	0.0008	0.0007	0.0009	0.0008	0.0008	0.0008	0.0007
CI lb	0.001	0.002	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001
CI ub	0.006	0.004	0.005	0.005	0.004	0.004	0.005	0.005	0.004	0.004	0.004	0.004
b_i	1.0405	1.0006	0.9743	1.0229	1.0107	0.9956	0.9754	1.002	1.0079	0.9663	1.0104	0.9775
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0304	0.016	0.0229	0.0249	0.0217	0.0218	0.0185	0.0246	0.0211	0.02	0.0212	0.0192
CI lb	0.981	0.969	0.929	0.974	0.968	0.953	0.939	0.954	0.966	0.927	0.969	0.94
CI ub	1.1	1.032	1.02	1.072	1.053	1.039	1.012	1.05	1.05	1.006	1.052	1.016
s_i	0.145	0.089	0.0594	0.1205	0.0445	0.1224	0.0837	0.1038	0.0617	0.0863	0.0707	0.0915
P-value	0.006	0.002	0.133	0.006	0.235	0.001	0.009	0.015	0.091	0.013	0.054	0.006
Std. Dev.	0.0522	0.0276	0.0394	0.0429	0.0373	0.0375	0.0318	0.0423	0.0364	0.0345	0.0365	0.0331
CI lb	0.042	0.035	-0.018	0.036	-0.029	0.049	0.021	0.02	-0.01	0.018	-0.001	0.026
CI ub	0.248	0.143	0.137	0.205	0.118	0.196	0.146	0.187	0.134	0.154	0.143	0.157
h_i	0.0376	0.1051	-0.1118	0.0623	0.1333	0.0789	-0.0228	0.0777	0.1364	0.0111	0.1128	0.0489
P-value	0.434	0	0.002	0.116	0	0.023	0.435	0.047	0	0.726	0.001	0.109
Std. Dev.	0.0479	0.0253	0.0362	0.0394	0.0342	0.0344	0.0292	0.0388	0.0334	0.0316	0.0335	0.0304
CI lb	-0.057	0.055	-0.183	-0.015	0.066	0.011	-0.08	0.001	0.07	-0.051	0.047	-0.011
CI ub	0.132	0.155	-0.04	0.14	0.201	0.147	0.035	0.154	0.202	0.074	0.179	0.109
m_i	-0.2129	-0.1319	-0.0527	-0.1859	-0.144	-0.11	-0.0902	-0.1703	-0.107	-0.0792	-0.1538	-0.0823
P-value	0	0	0.016	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0287	0.0151	0.0217	0.0236	0.0205	0.0206	0.0175	0.0232	0.02	0.0189	0.0201	0.0182
CI lb	-0.27	-0.162	-0.096	-0.233	-0.184	-0.151	-0.125	-0.216	-0.146	-0.117	-0.193	-0.118
CI ub	-0.156	-0.102	-0.01	-0.139	-0.103	-0.069	-0.056	-0.124	-0.068	-0.042	-0.114	-0.046
Adj R^2	0.9216	0.9734	0.9356	0.9428	0.9536	0.9508	0.9601	0.9416	0.9543	0.9527	0.9558	0.9578

Table 23: Carhart 4-factor regression results of the four different scenarios. The portfolios are sorted yearly based on the end-year wokeness scores (2005-2018) and the equal weighted monthly returns from the beginning of the year (2006-2019).

5.5.2 Fama and French 5-factor model

The Carhart 4-factor model seems to have slightly higher explanatory power than the 3-factor model. The 3- and 4-factor models do not account for the fact that profitable companies generate higher returns than non-profitable companies (Novy-Marx, 2013) or the fact that companies that increase their capital investment tend to have higher past returns (Titman, Wei, & Xie, 2004). The 5-factor model adjusts for these two factors, hence, we run the regressions again using the 5-factor model.

5.5.2.1 Value weighted portfolios

Table 24 shows the 5-factor results for the regressions on the value-weighted portfolios. The alpha is highest for the bottom 15 and lowest for the neutral 70, the same as in the 3- and 4-factor model. All alphas are significantly different from 0 with p-values below 0.001. The standard error is highest for the bottom 15, meaning that the bottom 15 and top 15 have a large overlap in the 95%-confidence intervals. The betas are all significantly different from 0 and they all have 1 included in the 95%-confidence interval. The coefficients for SMB are all relatively close to 0, and only the neutral 70 is significantly different from 0 with a p-value below 0.05. The coefficients for HML are all significantly different from 0, the value for the top 15 is negative and the other two portfolios have coefficients above 0. The coefficients for RMW are all relatively close to 0 and all have p-value above 0.05 meaning that 0 is included in the 95%-confidence intervals for all three portfolios. The coefficients for CMA are also all close to 0 with p-values above 0.1. The adjusted R-squared values indicate that the model is explaining the variation in data quite well. The adjusted R-squared values for neutral 70 and the top 15 are above 90%, while the bottom 15 has the lowest R-squared of 86.53%.

In scenario two, the highest alpha of 0.57% is for the 75-100 portfolio, and the lowest alpha of 0.27% is for the 50-75 portfolio. All alphas are significantly different from 0 with p-values below 0.05. The betas are below 1 for most portfolios and only 50-75 have 1 included in the 95%-confidence interval. The coefficients for SMB are all negative and most are significantly different from 0, except for the 75-100 portfolio. The coefficients for HML are all positive and 0-25 and 25-50 are significantly different from 0 at a 5%-level. The coefficient for the 75-100 portfolio is nearly significant with a p-value of 0.052. The coefficients for RMW are relatively close to 0, but only the 50-75 portfolio is significantly different from 0. The coefficients for CMA are all close to 0 and all have 0 included in the 95%-confidence interval. The adjusted R-squared values are all relatively high. The 25-50 portfolio has an adjusted R-squared value of 86.89% which is the only value below 90%.

In the third scenario, the top 30 portfolio has the highest alpha of 0.53%, closely followed by an alpha of 0.51% in the bottom 30 portfolio. The lowest alpha of 0.36% is in the neutral 40 portfolio. All alphas are significantly different from 0 with p-values below 0.001. The betas are all relatively close to 1, the bottom 30 and neutral 40 both have 1 included in the 95%-confidence intervals. The coefficients for SMB are all negative and only the top 30 is insignificant with a p-value of 0.188. The coefficients for HML are all positive and significantly different from 0 with p-values below 0.01. The coefficients for RMW are insignificant, negative, and close to 0 for the top 30 and bottom 30 with p-values above 0.7. For the neutral 40, the coefficient is positive and significantly different from 0. For the last factor, CMA, the coefficients are all relatively close to 0 and all have p-values above 0.05. The explanatory power of the model seems to be good for these three portfolios as they all have adjusted R-squared values above 92%.

In scenario four the alphas for the two portfolios are relatively close to one another as the alpha is 0.5% for the top 50 portfolio and 0.45% for the bottom 50 portfolio. Both alphas are significantly different from 0 with p-values below 0.001. The betas are both significantly different from 0, and relatively close to 1. However, 1 is only included in the 95%-confidence interval for the bottom 50. The coefficients for SMB are both negative and significantly different from 0. The coefficients for HML are both positive and significantly different from 0. The coefficients for RMW and CMA are all close to 0 and all have p-values above 0.2, indicating that we cannot reject that the coefficients are different from 0. The adjusted R-squared values are both relatively high and above 93%.

Value weighted wokeness portfolio: Fama and French 5-factor model

$$r_i - r_f = \alpha_i + b_i \mathrm{MktRF} + s_i SMB + h_i HML + r_i \mathrm{RMW} + c_i \mathrm{CMA} + \epsilon_i$$

	Bottom 15	Neutral 70	Top 15	0-25	25-50	50-75	75-100	Botom 30	Neutal 40	Top 30	Bottom 50	Top 50
a_i	0.006	0.0042	0.0053	0.0049	0.0038	0.0027	0.0057	0.0051	0.0036	0.0053	0.0045	0.005
P-value	0	0	0	0	0.005	0.006	0	0	0	0	0	0
Std. Dev.	0.0013	0.0007	0.001	0.001	0.0013	0.001	0.0009	0.0009	0.0008	0.0009	0.0009	0.0007
CI lb	0.003	0.003	0.003	0.003	0.001	0.001	0.004	0.003	0.002	0.004	0.003	0.004
CI ub	0.009	0.005	0.007	0.007	0.006	0.005	0.007	0.007	0.005	0.007	0.006	0.006
b_i	0.9562	0.981	0.9545	0.9243	1.0118	0.9359	0.9514	0.9537	0.9897	0.9514	0.9821	0.9558
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0356	0.0178	0.0279	0.0257	0.0357	0.0262	0.0235	0.0252	0.021	0.0239	0.0234	0.0188
CI lb	0.886	0.946	0.899	0.874	0.941	0.884	0.905	0.904	0.948	0.904	0.936	0.919
CI ub	1.027	1.016	1.01	0.975	1.082	0.988	0.998	1.004	1.031	0.999	1.028	0.993
s_i	-0.0499	-0.1916	-0.0235	-0.1199	-0.2452	-0.0936	-0.0418	-0.1903	-0.1735	-0.0532	-0.202	-0.0856
P-value	0.408	0	0.618	0.006	0	0.036	0.293	0	0	0.188	0	0.008
Std. Dev.	0.0601	0.0301	0.047	0.0434	0.0602	0.0442	0.0397	0.0426	0.0354	0.0403	0.0394	0.0317
CI lb	-0.169	-0.251	-0.116	-0.206	-0.364	-0.181	-0.12	-0.275	-0.243	-0.133	-0.28	-0.148
CI ub	0.069	-0.132	0.069	-0.034	-0.126	-0.006	0.036	-0.106	-0.103	0.026	-0.124	-0.023
h_i	0.1778	0.1664	-0.1137	0.1419	0.2259	0.0624	0.0787	0.1621	0.137	0.106	0.1968	0.0707
P-value	0.004	0	0.018	0.002	0	0.166	0.052	0	0	0.01	0	0.029
Std. Dev.	0.061	0.0306	0.0477	0.0441	0.0611	0.0448	0.0402	0.0432	0.036	0.0409	0.04	0.0322
CI lb	0.057	0.106	-0.208	0.055	0.105	-0.026	-0.001	0.077	0.066	0.025	0.118	0.007
CI ub	0.298	0.227	-0.019	0.229	0.346	0.151	0.158	0.247	0.208	0.187	0.276	0.134
r_i	0.0193	0.089	-0.0389	0.0308	0.1201	0.1738	-0.0208	-0.0027	0.1586	-0.022	0.0739	0.0518
P-value	0.84	0.064	0.602	0.655	0.21	0.014	0.741	0.968	0.005	0.731	0.239	0.304
Std. Dev.	0.0953	0.0477	0.0745	0.0688	0.0954	0.07	0.0628	0.0675	0.0562	0.0639	0.0625	0.0502
CI lb	-0.169	-0.005	-0.186	-0.105	-0.068	0.036	-0.145	-0.136	0.048	-0.148	-0.05	-0.047
CI ub	0.207	0.183	0.108	0.167	0.308	0.312	0.103	0.131	0.27	0.104	0.197	0.151
c_i	-0.0076	-0.0707	-0.0281	0.0273	-0.1228	0.0042	-0.0876	-0.0872	0.0041	-0.1283	-0.0706	-0.0258
P-value	0.944	0.19	0.738	0.725	0.255	0.957	0.217	0.253	0.948	0.076	0.317	0.649
Std. Dev.	0.1073	0.0537	0.0839	0.0775	0.1074	0.0788	0.0708	0.076	0.0633	0.0719	0.0704	0.0566
CI lb	-0.22	-0.177	-0.194	-0.126	-0.335	-0.151	-0.227	-0.237	-0.121	-0.27	-0.21	-0.138
CI ub	0.204	0.035	0.138	0.18	0.089	0.16	0.052	0.063	0.129	0.014	0.068	0.086
Adj R^2	0.8653	0.9614	0.9072	0.9163	0.8689	0.9106	0.9349	0.9235	0.9468	0.9334	0.9366	0.9557

Table 24: Fama and French 5-factor regression results of the four different scenarios. The portfolios are sorted yearly based on the end-year wokeness scores (2005-2018) and the value weighted monthly returns from the beginning of the year (2006-2019).

5.5.2.2 Equally weighted

In Table 25, we show the Fama and French 5-factor regression results for the equally weighted portfolios. All portfolios exhibit a positive alpha. The alphas are significantly different from 0 for all portfolios except for the neutral 40 which has a p-value of 0.054. All alphas are lower in the equally weighted portfolios. The 95%-confidence intervals for all alphas in the equally weighted portfolios are overlapping meaning we cannot be certain that the alphas differ from one another.

In scenario one, the alpha is highest for the bottom 15 and lowest for the neutral 70. In scenario two the alpha for 75-100 is highest and equal to 0.0031, but closely followed by the 0-25 with an alpha of 0.003. In the third scenario, the highest alpha is for the bottom 30 and the lowest is for the neutral 40. In the fourth scenario the alphas are very similar, but highest for bottom 50.

The betas are close to 1 and significantly different from 0 and most portfolios have 1 included in the 95%-confidence interval. Contrary to the value-weighted portfolios all equally weighted portfolios have a positive SMB coefficient and most of the coefficients are significantly different from 0. The HML coefficients are quite similar to the value-weighted portfolios except for the HML coefficient for the top 15 portfolio as the value is negative. Almost all of the coefficients are significantly different from 0. There is not a clear pattern in the RMW coefficients which is confirmed by none of the coefficients being significantly different from 0. The same can be seen for the CMA coefficients as none of the factor coefficients are significantly different from 0. As none of the RMW and CMA factors are significant we cannot be certain that these factors increase the explanatory power of the model. The adjusted R-squared values range from 92% to 96%, except for the bottom 15 which has an adjusted R-squared value of 89.6%

A general observation for the equally weighted portfolios is that the confidence intervals overlap in all scenarios. Furthermore, the alphas standard deviations for the bottom portfolios are higher than for the top portfolios. This indicates higher uncertainty about the true value. The adjusted R-squared values for the equally weighted portfolios are on average higher than for the value-weighted portfolios. The adjusted R-squared is highest for the neutral 70, which is also the portfolio that has the highest number of companies included. There seems to be a general trend that the adjusted R-squared increases as the portfolio size increases and the bottom portfolios have lower adjusted R-squared values than the top portfolios.

Equal weighted wokeness portfolio: Fama and French 5-factor model

$$r_i - r_f = \alpha_i + b_i\mathrm{MktRF} + s_i SMB + h_i HML + r_i\mathrm{RMW} + c_i\mathrm{CMA} + \epsilon_i$$

	Bottom 15	Neutral 70	Top 15	0-25	25-50	50-75	75-100	Botom 30	Neutal 40	Top 30	Bottom 50	Top 50
a_i	0.0035	0.0023	0.0027	0.0030	0.0023	0.0018	0.0031	0.0030	0.0017	0.0024	0.0024	0.0022
P-value	0.012	0.003	0.004	0.011	0.019	0.047	0.000	0.007	0.054	0.004	0.014	0.006
Std. Dev.	0.0014	0.0008	0.0009	0.0011	0.0010	0.0009	0.0008	0.0011	0.0009	0.0008	0.0010	0.0008
CI lb	0.001	0.001	0.001	0.001	0	0	0.002	0.001	0	0.001	0.001	0.001
CI ub	0.006	0.004	0.004	0.005	0.004	0.004	0.005	0.005	0.004	0.004	0.004	0.004
b_i	1.0914	1.0422	0.9931	1.0719	1.0612	1.0304	1.0006	1.0488	1.0437	0.9916	1.0574	1.0028
P-value	0	0	0	0	0	0	0	0	0	0	0	0
Std. Dev.	0.0368	0.0202	0.0246	0.0307	0.0259	0.0246	0.0209	0.0298	0.0240	0.0222	0.0260	0.0214
CI lb	1.019	1.002	0.945	1.011	1.010	0.982	0.959	0.990	0.996	0.948	1.006	0.961
CI ub	1.164	1.082	1.042	1.133	1.112	1.079	1.042	1.107	1.091	1.035	1.109	1.045
s_i	0.1529	0.1071	0.0610	0.1268	0.0676	0.1422	0.0914	0.1110	0.0819	0.0950	0.0847	0.1035
P-value	0.015	0.002	0.143	0.016	0.123	0.001	0.011	0.028	0.045	0.012	0.055	0.005
Std. Dev.	0.0620	0.0341	0.0415	0.0519	0.0437	0.0416	0.0353	0.0502	0.0405	0.0374	0.0438	0.0361
CI lb	0.030	0.040	-0.021	0.024	-0.019	0.060	0.022	0.012	0.002	0.021	-0.002	0.032
CI ub	0.275	0.174	0.143	0.229	0.154	0.224	0.161	0.210	0.162	0.169	0.171	0.175
h_i	0.1524	0.1854	-0.0863	0.1611	0.2151	0.1461	0.0389	0.1694	0.1966	0.0532	0.1941	0.0968
P-value	0.017	0	0.042	0.003	0	0.001	0.279	0.001	0	0.163	0	0.009
Std. Dev.	0.0630	0.0346	0.0421	0.0527	0.0443	0.0422	0.0358	0.0510	0.0411	0.0379	0.0445	0.0367
CI lb	0.028	0.117	-0.169	0.057	0.128	0.063	-0.032	0.069	0.116	-0.022	0.106	0.024
CI ub	0.277	0.254	-0.003	0.265	0.303	0.229	0.110	0.27	0.278	0.128	0.282	0.169
r_i	-0.0498	0.0693	0.0289	-0.0199	0.0871	0.0804	0.0380	-0.0037	0.0656	0.0399	0.0285	0.0475
P-value	0.613	0.202	0.661	0.809	0.210	0.224	0.498	0.963	0.308	0.501	0.682	0.408
Std. Dev.	0.0983	0.0541	0.0657	0.0822	0.0692	0.0659	0.0559	0.0796	0.0642	0.0592	0.0694	0.0573
CI lb	-0.244	-0.037	-0.101	-0.182	-0.050	-0.050	-0.072	-0.161	-0.061	-0.077	-0.109	-0.066
CI ub	0.144	0.176	0.159	0.142	0.224	0.210	0.148	0.153	0.192	0.157	0.166	0.161
c_i	0.0169	-0.0103	0.0092	0.0254	0.0289	-0.0287	-0.0362	0.0235	0.0098	0.0000	0.0365	-0.0144
P-value	0.879	0.866	0.901	0.784	0.711	0.7	0.567	0.793	0.893	1.000	0.642	0.823
Std. Dev.	0.1108	0.0609	0.0740	0.0926	0.0779	0.0742	0.0630	0.0896	0.0723	0.0667	0.0782	0.0645
CI lb	-0.202	-0.131	-0.137	-0.158	-0.125	-0.175	-0.161	-0.153	-0.133	-0.132	-0.118	-0.142
CI ub	0.236	0.110	0.155	0.208	0.183	0.118	0.088	0.201	0.152	0.132	0.191	0.113
Adj R^2	0.8959	0.9617	0.9329	0.9213	0.9400	0.9429	0.9536	0.9225	0.9467	0.9476	0.9401	0.9528

Table 25: Fama and French 5-factor regression results of the four different scenarios. The portfolios are sorted yearly based on the end-year wokeness scores (2005-2018) and the equal weighted monthly returns from the beginning of the year (2006-2019)..

Comparing the 5-factor model to the 4-factor and the 3-factor models we see a similar performance. The 4-factor model has slightly higher explanatory power seen by higher adjusted R-squared values. The coefficients for RMW and CMA seem to have very little effect on the model as only two out of 24 are significantly different from 0. The MOM factor seems to have a little higher explanatory power with 4 out of 12 being significantly different from 0. However, adding the MOM factor leads to a drop in the significance of the HML coefficients as only 7 of the 12 is now significant in the 4-factor model.

5.6 Time divided performance of the wokeness portfolios

To see if our results are affected by the period we have chosen for our analysis, we decide to divide our sample period into two subperiods. The first period ranges from 2006-2012 and the second ranges from 2013-2019. We chose to include only the 15-70-15 portfolios and the 50-50 portfolios in this part of the analysis as they represent the most extreme and average wokeness portfolios. Figure 30 shows the cumulative returns for the two periods for the bottom 15, neutral 70, and top 15 portfolios. The cumulative returns for the bottom and top 50 portfolios for the two subperiods can be seen in Figure 31.

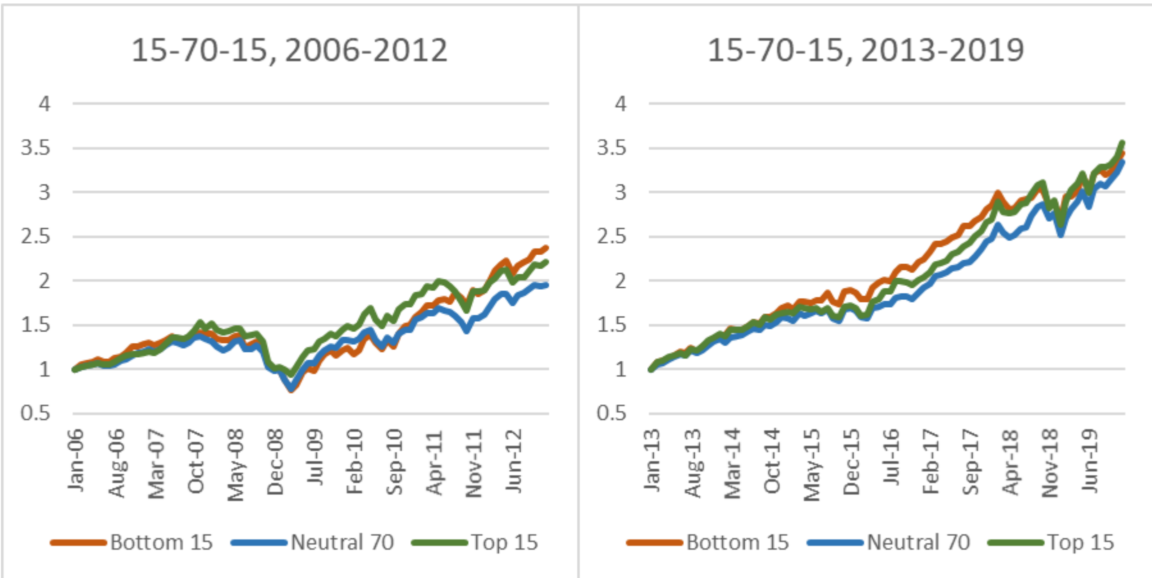

Figure 30: Time divided cumulative returns for the bottom 15, neutral 70, and top 15 portfolios.

From Figure 30 we can see that the cumulative returns for the period 2006-2012 look different from the cumulative returns in 2013-2019. In the first subperiod the top 15 portfolio outperformed the other portfolios from 2006 until mid-2011. The bottom 15 portfolio surpassed the top 15 portfolio at the end of 2011 and ended up as the best performing portfolio at the end of the subperiod. The neutral 70 portfolio ended up performing worse than the other two portfolios from late 2010 until the end of the subperiod in 2012.

The cumulative returns from 2013-2019 show that the performance of all portfolios were quite similar from the beginning of 2013 until early 2015. The largest variation in performance occurred between early 2015 and the stock market dip in late 2018. During this period, the bottom 15 portfolio outperformed the other two portfolios. The top 15 portfolio started performing better than the bottom 15 portfolio in 2018 just before the stock market dip and continued to outperform the other two portfolios until the end of the subperiod. The neutral 70 portfolio seemed to perform worse than the other two portfolios during the whole subperiod.

When comparing the subperiods to the whole period (Figure 26) we see that the clear outperformance of the bottom 15 portfolio cannot be seen when the periods are divided, suggesting that the starting point and length of the sampling period has a profound effect on the returns.

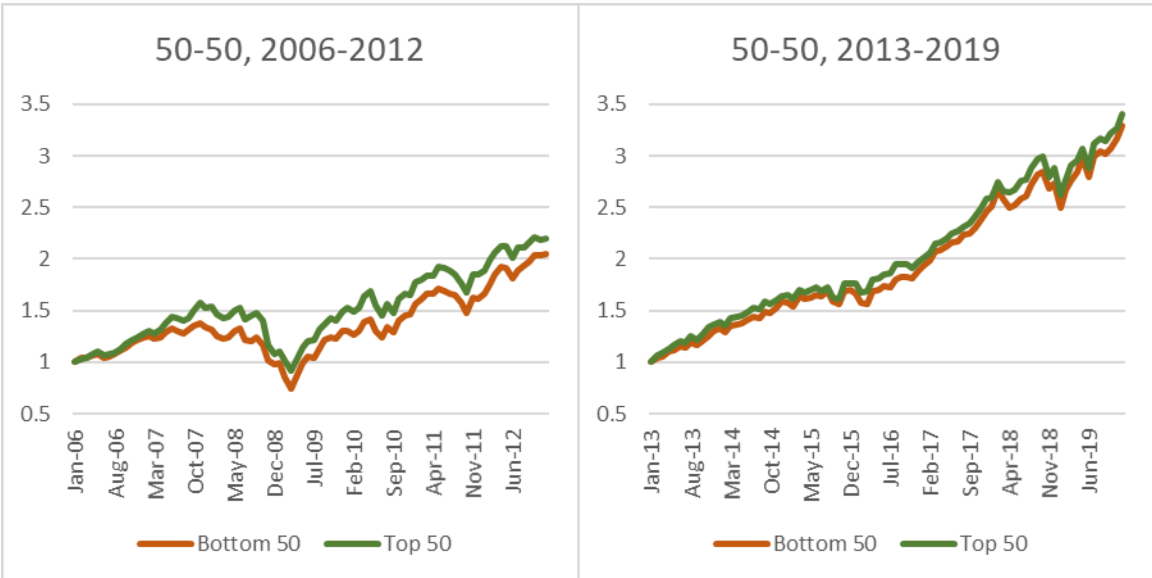

Figure 31: Time divided cumulative returns for the bottom 50 and top 50 portfolios

From Figure 31 it is clear that the top 50 portfolio is performing better than the bottom 50 portfolio during both subperiods. This is similar to the trend seen in the whole period (Figure 29).

5.7 Time divided regression results

We see from Table 20-25 that the 3-, 4-, and 5-factor models yield similar alphas which is why we choose to assess the time divided portfolios only using the 5-factor model. Since adding factors in the 4- and 5-factor model does not improve the variance that can be explained by the model, we can argue that the factors are not adding any value to the model. However, as our objective is to compare the alphas, the model selection cannot be based solely on the variance explained by the model. Table 26 shows the regression results for the Fama and French 5-factor model for the time divided bottom 15, neutral 70, and top 15 portfolios.

Comparing the results between the two subperiods, we see that from 2006 to 2012 the top 15 has the highest alpha of 0.69%, followed by the bottom 15 portfolio and the neutral portfolio. In the second subperiod, the bottom 15 portfolio has the highest alpha of 0.47%, followed by the top 15 and neutral portfolio. The alphas are in general higher in 2006-2012 compared to the alphas in 2013-2019. All alphas are significantly different from 0 with p-values below 0.05. There is a clear difference in the alphas in the two subperiods compared to the whole period.

The betas are all quite close to one, except the beta for the top 15 portfolio in 2006-2012 which has a beta of 0.8972. All beta coefficients are significantly different from 0 with p-values below 0.001. The SMB coefficients are all negative and significantly different from 0, except for the top 15 portfolios in both subperiods. The HML coefficient is positive for the bottom 15 and neutral 70 portfolios in both subperiods and negative for the top 15 portfolios in both subperiods. However, the coefficients are only significant in the bottom 15 and neutral 70 portfolio in the first subperiod. The RMW coefficients are positive for all portfolios except the top 15 in the subperiod 2006-2012 and the bottom 15 portfolio in 2013-2018. The RMW coefficients are only significant for the bottom 15 portfolios in both subperiods and the neutral 70 portfolios in 2013-2019. The CMA coefficients are mostly negative, however, none of the coefficients are significantly different from 0. The adjusted R-squared values range from 89% to 98%.

Time divided value weighted wokeness portfolio: Fama and French 5-factor model						
$r_i - r_f = \alpha_i + b_i\mathrm{MktRF} + s_iSMB + h_iHML + r_i\mathrm{RMW} + c_i\mathrm{CMA} + \epsilon_i$						
	2006-2012			2013-2019		
	Bottom 15	**Neutral 70**	**Top 15**	**Bottom 15**	**Neutral 70**	**Top 15**
a_i	0.0049	0.0045	0.0069	0.0047	0.0034	0.0035
P-value	0.025	0	0	0.001	0	0.005
Std. Dev.	0.0021	0.0012	0.0018	0.0013	0.0005	0.0012
CI lb	0.001	0.002	0.003	0.002	0.002	0.001
CI ub	0.009	0.007	0.010	0.007	0.004	0.006
b_i	1.0361	0.9849	0.8972	0.9175	0.9737	1.0208
P-value	0	0	0	0	0	0
Std. Dev.	0.0555	0.0310	0.0458	0.0397	0.0142	0.0367
CI lb	0.926	0.923	0.806	0.839	0.945	0.948
CI ub	1.147	1.047	0.988	0.997	1.002	1.094
s_i	-0.0440	-0.2176	-0.0276	-0.1434	-0.1670	-0.0184
P-value	0.643	0	0.725	0.023	0	0.749
Std. Dev.	0.0948	0.0530	0.0782	0.0619	0.0221	0.0572
CI lb	-0.233	-0.323	-0.183	-0.267	-0.211	-0.132
CI ub	0.145	-0.112	0.128	-0.020	-0.123	0.095
h_i	0.3224	0.2774	-0.0905	0.0151	0.0017	-0.1313
P-value	0	0	0.206	0.827	0.944	0.043
Std. Dev.	0.0860	0.0481	0.0709	0.0689	0.0246	0.0636
CI lb	0.151	0.182	-0.232	-0.122	-0.047	-0.258
CI ub	0.494	0.373	0.051	0.152	0.051	-0.005
r_i	0.4659	0.1731	-0.1651	-0.2837	0.0898	0.0185
P-value	0.004	0.052	0.206	0.006	0.014	0.841
Std. Dev.	0.1568	0.0877	0.1294	0.0996	0.0356	0.0920
CI lb	0.154	-0.001	-0.423	-0.482	0.019	-0.165
CI ub	0.778	0.348	0.092	-0.085	0.161	0.202
c_i	0.1728	-0.0527	-0.0150	-0.0661	-0.0118	-0.0552
P-value	0.284	0.558	0.910	0.561	0.771	0.599
Std. Dev.	0.1602	0.0895	0.1322	0.1132	0.0405	0.1046
CI lb	-0.146	-0.231	-0.278	-0.291	-0.092	-0.263
CI ub	0.492	0.126	0.248	0.159	0.069	0.153
Adj. R^2	0.8901	0.9591	0.9020	0.8823	0.9843	0.9172

Table 26: Fama and French 5-factor regression results for the value weighted bottom 15, neutral 70, and top 15 portfolios for the subperiods 2006-2012 and 2013-2019.

Table 27 shows the time divided regression result for the equally weighted portfolios. Similar to the value-weighted scenarios, the alpha is highest for the top 15 portfolio in the first subperiod and highest for the bottom 15 portfolio in the second subperiod. Most alphas are significantly different from 0, except for the bottom 15 in the first subperiod and the top 15 in the second subperiod.

The betas are all relatively close to 1 and significantly different from 0. The remaining factor coefficients exhibit little consistency, and most coefficients are insignificant. The adjusted R-squared for all models are in the range of 89%-98%.

Time divided equal weighted wokeness portfolio: Fama and French 5-factor model

$$r_i - r_f = \alpha_i + b_i\text{MktRF} + s_i SMB + h_i HML + r_i\text{RMW} + c_i\text{CMA} + \epsilon_i$$

	2006-2012			2013-2019		
	Bottom 15	**Neutral 70**	**Top 15**	**Bottom 15**	**Neutral 70**	**Top 15**
a_i	0.0034	0.0036	0.0043	0.0034	0.0014	0.0017
P-value	0.162	0.007	0.005	0.017	0.024	0.145
Std. Dev.	0.0024	0.0013	0.0015	0.0014	0.0006	0.0012
CI lb	-0.001	0.001	0.001	0.001	0.000	-0.001
CI ub	0.008	0.006	0.007	0.006	0.003	0.004
b_i	1.1922	1.0420	0.9752	0.9767	1.0043	0.9974
P-value	0.000	0.000	0.000	0.000	0.000	0.000
Std. Dev.	0.0616	0.0342	0.0388	0.0418	0.0187	0.0352
CI lb	1.069	0.974	0.898	0.893	0.967	0.927
CI ub	1.315	1.110	1.052	1.060	1.042	1.067
s_i	0.1471	0.1627	0.0986	0.1293	0.0764	0.0322
P-value	0.166	0.007	0.141	0.051	0.011	0.559
Std. Dev.	0.1052	0.0583	0.0662	0.0651	0.0291	0.0549
CI lb	-0.062	0.047	-0.033	-0.000	0.018	-0.077
CI ub	0.357	0.279	0.230	0.259	0.134	0.142
h_i	0.2261	0.2692	-0.0997	0.0198	0.0135	-0.0877
P-value	0.020	0.000	0.101	0.785	0.679	0.156
Std. Dev.	0.0955	0.0529	0.0601	0.0725	0.0324	0.0611
CI lb	0.036	0.164	-0.219	-0.124	-0.051	-0.209
CI ub	0.416	0.375	0.020	0.164	0.078	0.034
r_i	0.2278	0.0654	-0.0673	-0.1709	0.1073	0.0637
P-value	0.195	0.500	0.541	0.107	0.025	0.473
Std. Dev.	0.1741	0.0965	0.1096	0.1048	0.0469	0.0884
CI lb	-0.119	-0.127	-0.285	-0.380	0.014	-0.112
CI ub	0.575	0.258	0.151	0.038	0.201	0.240
c_i	-0.0014	-0.1447	-0.0895	0.0930	0.1696	0.0742
P-value	0.994	0.146	0.426	0.438	0.002	0.463
Std. Dev.	0.1779	0.0986	0.1120	0.1192	0.0533	0.1005
CI lb	-0.356	-0.341	-0.312	-0.144	0.064	-0.126
CI ub	0.353	0.052	0.133	0.330	0.276	0.274
Adj R^2	0.9055	0.9635	0.9392	0.8938	0.9765	0.9190

Table 27: Fama and French 5-factor regression results for the equally weighted bottom 15, neutral 70, and top 15 portfolios for the subperiods 2006-2012 and 2013-2019

Table 28 shows the results of the Fama and French 5-factor regression of the bottom and top 50 portfolios. The alphas are the highest in the top 50 portfolios in both subperiods. Similarly to the other time divided portfolios the alphas are higher in the first subperiod. All alphas are significantly different from 0 with p-values below 0.01.

All betas are close to 1, and all beta coefficients are significantly different from 0 with p-values under 0.001. All portfolios except for the bottom 50 in 2013-2019 have a beta of 1 included in the 95%-confidence intervals.

Time divided value weighted wokeness portfolio: Fama and French 5-factor model				
$r_i - r_f = \alpha_i + b_i\text{MktRF} + s_i SMB + h_i HML + r_i\text{RMW} + c_i\text{CMA} + \epsilon_i$				
	2006-2012		2013-2019	
	Bottom 50	**Top 50**	**Bottom 50**	**Top 50**
a_i	0.0048	0.006	0.0033	0.0039
P-value	0.003	0	0	0
Std. Dev.	0.0016	0.0011	0.0005	0.0008
CI lb	0.002	0.004	0.002	0.002
CI ub	0.008	0.008	0.004	0.005
b_i	1.0089	0.9504	0.9634	0.952
P-value	0	0	0	0
Std. Dev.	0.041	0.0296	0.0165	0.0242
CI lb	0.927	0.891	0.93	0.904
CI ub	1.091	1.009	0.996	1
s_i	-0.2683	-0.0501	-0.1572	-0.123
P-value	0	0.325	0	0.002
Std. Dev.	0.07	0.0506	0.0257	0.0377
CI lb	-0.408	-0.151	-0.208	-0.198
CI ub	-0.129	0.051	-0.106	-0.048
h_i	0.3294	0.1516	0.0159	-0.0626
P-value	0	0.001	0.58	0.14
Std. Dev.	0.0635	0.0459	0.0286	0.042
CI lb	0.203	0.06	-0.041	-0.146
CI ub	0.456	0.243	0.073	0.021
r_i	0.2383	0.0926	0.0421	0.0264
P-value	0.043	0.272	0.312	0.665
Std. Dev.	0.1158	0.0837	0.0414	0.0607
CI lb	0.008	-0.074	-0.04	-0.094
CI ub	0.469	0.259	0.124	0.147
c_i	0.0084	-0.0826	-0.0613	0.0788
P-value	0.943	0.337	0.197	0.257
Std. Dev.	0.1183	0.0855	0.0471	0.069
CI lb	-0.227	-0.253	-0.155	-0.059
CI ub	0.244	0.088	0.032	0.216
Adj R^2	0.9329	0.9612	0.9788	0.9538

Table 28: Fama and French 5-factor regression results for the value weighted bottom 50, and top 50 portfolios for the subperiods 2006-2012 and 2013-2019.

All SMB coefficients are negative and significantly different from 0 except the top 50 portfolio in 2006-2012. The HML factor coefficients are positive for most portfolios but only significantly different from 0 in the first subperiod. The RMW factor coefficients are all positive but only significant on a 5%-level for the bottom 50 portfolio in 2006-2012. The CMA coefficients are all insignificant. The Adjusted R-squared values are all high, ranging from 93% to 98%.

The results from the time split regression do not vary much from the results of the 5-factor regression for the whole period. The time divided regression result implies that the top 50 portfolio outperforms the bottom 50 portfolio in both subperiods.

Time divided equal weighted wokeness portfolio: Fama and French 5-factor model

$$r_i - r_f = \alpha_i + b_i\mathrm{MktRF} + s_iSMB + h_iHML + r_i\mathrm{RMW} + c_i\mathrm{CMA} + \epsilon_i$$

	2006-2012		2013-2019	
	Bottom 50	**Top 50**	**Bottom 50**	**Top 50**
a_i	0.0030	0.0043	0.0033	0.0039
P-value	0.073	0.000	0.000	0.000
Std. Dev.	0.0017	0.0011	0.0005	0.0008
CI lb	-0.000	0.002	0.002	0.002
CI ub	0.006	0.006	0.004	0.005
b_i	1.1043	1.0054	0.9634	0.9520
P-value	0.000	0.000	0.000	0.000
Std. Dev.	0.0435	0.0293	0.0165	0.0242
CI lb	1.018	0.947	0.930	0.904
CI ub	1.191	1.064	0.996	1.000
s_i	0.1189	0.1812	-0.1572	-0.1230
P-value	0.113	0.001	0.000	0.002
Std. Dev.	0.0742	0.0500	0.0257	0.0377
CI lb	-0.029	0.082	-0.208	-0.198
CI ub	0.267	0.281	-0.106	-0.048
h_i	0.2798	0.1370	0.0159	-0.0626
P-value	0.000	0.003	0.580	0.140
Std. Dev.	0.0674	0.0454	0.0286	0.0420
CI lb	0.146	0.047	-0.041	-0.146
CI ub	0.414	0.227	0.073	0.021
r_i	0.1538	-0.0138	0.0421	0.0264
P-value	0.214	0.869	0.312	0.665
Std. Dev.	0.1228	0.0828	0.0414	0.0607
CI lb	-0.091	-0.178	-0.040	-0.094
CI ub	0.398	0.151	0.124	0.147
c_i	-0.0170	-0.2135	-0.0613	0.0788
P-value	0.892	0.014	0.197	0.257
Std. Dev.	0.1255	0.0845	0.0471	0.0690
CI lb	-0.267	-0.382	-0.155	-0.059
CI ub	0.233	-0.045	0.032	0.216
Adj R^2	0.9455	0.9704	0.9499	0.9330

Table 29: Fama and French 5-factor regression results for the equal weighted bottom 50, and top 50 portfolios for the subperiods 2006-2012 and 2013-2019.

Table 29 shows the regression results for the equally weighted portfolios for the two subperiods. The alphas are highest for the top portfolios in both subperiods, however, the difference between the alphas in the two subperiods is not as pronounced. All alphas are significantly different from 0 except in the bottom 50 portfolio.

The betas are all significant and close to 1. Similarly to the other equally weighted portfolios, there is no clear pattern in the remaining factors. There are slightly more significant coefficients in the first subperiod. The adjusted R-squared values are high, ranging from 93% to 97%.

6 Discussion

6.1 SH 1 Woke companies are more likely to donate to the Democrats

Similarly to the reference article, we find that blue companies donate more to the Democrats. Contrary to the reference article, we find that woke companies, generally prefer the Democrats. Our analysis suggests that the wokest companies in consumer-facing, healthcare, and technology prefer the Democrats; however, the wokest companies in energy and utility, industrial, and finance seem to prefer the Republicans. When all industries are combined (Figure 17), the wokest companies clearly prefer the Democrats. The finance industry generally has the lowest average wokeness scores through time. This is the only industry that tends to donate less to the Democrats as the wokeness score increases. The blue companies seem to be driving the downwards sloping trend. The reason could be that in this industry there is a large concentration of companies in New York and the surrounding states making the majority of the companies blue. As companies tend to donate more to the party that is more popular in their home state we, similarly to the reference article, review how much red and blue companies separately donate to each party based on wokeness scores. If all blue companies in the finance industry made a donation of $100,000 those companies with a wokeness score of 1 would on average give $73,000 to the Democrats, while companies with a wokeness score of 10 predictably would give $26,000 to the Democrats. A red company with a wokeness score of 1 would only donate $19,000 to the Democrats while a company with a wokeness score of 10 would donate $50,000. This indicates that, in the finance industry, woke and red companies seem to prefer the Democrats more than woke and blue companies.

The technology industry has the highest average wokeness score though time. The same $100,000 donation by blue companies with a wokeness score of 1, would yield a donation of $43,000 to the Democrats. A blue company with a wokeness score of 10 would donate all to the Democrats. The same donation by a red company with a wokeness score of 1 (10), would result in a donation of $52,000 ($55,000). Thus, all woke companies prefers the Democrats in the technology industry – no matter color.

When all industries are combined, the $100,000 donation from blue companies with a woke score of 1 would yield a donation of $36,000 to the Democrats. A company with a wokeness score of 10 would donate $81,000 to the Democrats. Red companies with a wokeness score of 1 (10) would donate $13,000 ($63,000) to the Democrats. This indicates that, despite color, all woke companies prefer the Democrats.

Overall, blue companies in most industries prefer to donate the majority of their money to the Democrats. All industries combined, the wokest companies prefer the Democrats, despite the color of the state where their headquarters are placed.

6.2 SH 2: The wokeness score of a company is consistent through time

The wokeness score is relatively inconsistent over time. The ESG score indicates that companies are striving to improve over time; however, the improvement seems to be mainly on paper as the controversies score shows that even the best companies have controversies. A constant striving to improve ESG performance will lead to a high turnover of companies in all portfolios. However, despite the continuously improving ESG scores, the average controversies are increasing over time. This will make some companies that are seemingly good to end up in the bottom portfolio. This suggests that some companies are trying to greenwash, as the ESG score is based on companies' own reporting. The influence of the donation score is relatively inconsistent.

The inconsistency of the wokeness score means that an investor cannot just invest in a woke company in 2018 and expect this company to keep a high score in future years. An investor employing a high (low) wokeness strategy has to rebalance her portfolios yearly.

6.3 SH 3 Woke companies have higher excess return than the market

When comparing the excess returns of the portfolios to the market return we notice that the excess returns for all portfolios are positive, including the excess returns for the time divided portfolios. All alphas in the value-weighted portfolios are significant. In the equally weighted portfolios most alphas are significant. We find it unlikely that all portfolios drastically outperform the market since the companies in the S&P 500 account for around 80% of the total market cap for the market (S&P Dow Jones Indices, 2020), hence we expect that they would yield similar returns. We rationalize that some of the excess returns could be due to survivorship bias[4] in our data. As we limit the companies we analyze to the constituents of the S&P 500 in 2020, we effectively exclude all companies that have been removed from the index between 2005 and 2019. During the period 2005-2019, 225 companies have been removed from the index, which is an average of 16 companies per year (S&P Dow Jones Indices, 2020). 117 companies were removed as they were acquired by another company, in many instances the acquiring companies were already included in the S&P 500. 49 companies were removed due to bad financial performance, and only 2 were removed due to bankruptcy (S&P Dow Jones Indices, 2020).

Since nearly half of the constituents of the S&P 500 have changed in the previous 15 years, we can assume that the companies that managed to stay until 2020 are companies that perform persistently well, as otherwise they would have been dropped from the index at some point. If a company is removed from the index, a new financially sound company is added. We investigate if there is a clear trend in the wokeness scores assigned to the newly included companies in the year of inclusion to the S&P 500. Most of the newly included companies end up being excluded from our sample due to missing data. For example, in 2005-2006 none of the newly added companies are included in our sample. In 2013, 18 companies were added to the index but only 4 of these are included in our sample. Of the 26 companies that were added in 2017, 19 are included in our sample. 10 of the companies were in the bottom 50 portfolio and 9 were in the top 50 portfolio, indicating no consistent pattern on how the newly added S&P 500 companies perform in our wokeness index in the year of their inclusion.

Another observation that suggests the existence of the survivorship bias is that the excess returns for 2006-2012 are generally higher than for 2013-2019. Of the S&P 500 companies only 52.5% (in 2006) to 74.8% (in 2012) is included in our sample, thus, there are only a few “surviving” companies left in 2020 which likely yields some of the high excess return. We excluded fewer companies from

[4] Corporate Finance Institute (2020) defines survivorship bias as “…a type of sample selection bias that occurs when a data set only considers “surviving” or existing observations and fails to consider observations that already ceased to exist.”

the later subperiod, however, the results are probably still affected by the survivorship bias but not as severely as the results from 2006-2012.

Due to the bias, we cannot trust the significance of the results, thus we cannot compare the excess returns of our portfolios to the market. We can still compare the financial performance of the wokeness portfolios to each other.

6.4 H1 Woke companies have higher excess returns than their less woke peers

In this section, we first discuss the results of the value-weighted portfolios after which we compare the results to the results of the equally weighted portfolios. Furthermore, we discuss the performance of the time divided portfolios and, lastly, we reflect upon the shape of the relationship between wokeness and financial performance.

6.4.1 Value weighted portfolios

The cumulative returns of the various portfolios indicate that the strategy for obtaining the highest returns, in the different portfolio scenarios, is investing in the bottom 15, 75-100, top 30, and top 50 portfolios. This observation is further validated by the 3-, 4-, and 5-factor regression results in Tables 20, 22, and 24 where the excess returns are the highest for the bottom 15, 75-100, top 30, and top 50 portfolios. The investment strategy with the highest excess return is investing in the bottom 15 portfolio. However, we cannot be sure that the alphas are significantly different from each other as the confidence intervals in all scenarios overlap. As the portfolio sizes increase, the alphas show a tendency to decrease, which can be seen both from the regression results and the cumulative returns.

There are a few possible reasons why the bottom 15 portfolio outperforms all other portfolios. First, the distribution of company weights is different in the bottom 15 portfolio when compared to the top 15 portfolio. There are 2-5 companies, such as Facebook, Berkshire Hathaway, and Visa, that account for around 40% of the whole portfolio weight, thus it is only a few companies that drive the majority of the returns of the portfolio. Facebook (since its inclusion in the S&P 500) and Berkshire Hathaway are the most consistent companies in the bottom portfolios. The same characteristics cannot be seen in the top 15 portfolio nor the bigger portfolios. When the portfolio sizes increase, the portfolio weights that these big companies account for decrease, diluting the effect that these companies have on the total monthly return of the portfolio.

Another reason for the outperformance of the bottom 15 portfolio, could be that according to Brammer et al. (2006) investors are willing to forgo some returns to feel morally at ease with their investment strategy, suggesting that investors accept lower returns for socially responsible investments. Investors might also demand higher returns due to the higher risks of non-responsible stocks as there is, for example, a higher probability of litigation at some point in the future (Hong & Kacperczyk, 2009). However, the bottom portfolio only outperforms the top portfolios in one instance in the value-weighted portfolios. As the bottom 15 contains the lowest number of companies, the portfolio construction is more likely to be the explanation for the high excess return.

The overall results indicate that in most cases, the wokest companies have higher excess returns than less woke companies. The ESG scores provide a possible explanation for this pattern as previous literature suggests that companies with high ESG scores tend to perform better than companies with low ESG scores. According to Fulton et al. (2012) companies with high CSR or ESG scores have a lower cost of capital in terms of equity and debt which leads to higher risk-adjusted returns. Investors also note that if a company is making an effort to recognize, for example, environmental concerns and energy efficiency, these efforts might be a way for investors to capitalize on future environmental legislations (Fulton et al. 2012). Furthermore, corporate social reputation is identified as being one of the strongest drivers of financial returns (Busch & Friede, 2017).

Our data suggests that companies in the top-performing wokeness portfolios tend to have high ESG scores indicating that a part of the excess returns can be attributed to this score. However, as our wokeness index does not consist solely of ESG scores we need to investigate further why the wokest companies usually perform better than less woke companies.

Our analysis shows that companies in the bottom portfolios tend to have a low Controversies score. Controversies tend to affect companies negatively and according to Capelle-Blancard and Petit (2019), every piece of negative news related to ESG factors will decrease the market cap of a company, on average, by 0.1%.

As seen from Table 11 there are is an overrepresentation of blue companies in the top portfolios and an overrepresentation of red companies in the bottom portfolios. Rubin (2008) finds that blue companies tend to have higher CSR scores which might explain why we see more blue companies at the top. Additionally as seen from figure 14-18 blue companies tend to donate more to the Democrats which further increases the wokeness scores of these companies.

A part of the excess returns of the top portfolios might be influenced by the fact that companies donating to a certain politician or political party tend to experience higher excess returns if that candidate or the party wins the election (Faccio & Parsley, 2009 and Goldman et al., 2009). The duration of our sample is 14 years, and out of those there has been a Democratic president for 8 years. The Democrats have had Senate and House majority for 8 and 4 years, respectively. This could indicate that companies that have donated mostly to the Democrats might have benefitted from the previous election results. However, it is difficult to conclude anything significant as political donations might also reflect agency problems (Aggerwal et al.,2012).

6.4.2 Equal weighted portfolios

Our results suggest that the value-weighted portfolios always yield a higher excess return than the equally weighted portfolios. This indicates that the size of companies influences the excess returns. We see that size also influences excess returns in the equally weighted portfolios as the bottom portfolios, which include larger companies on average, have higher excess returns than the neutral and top portfolios.

Other reasons for the higher excess returns in the bottom portfolios could be that investors are ready to forgo some returns by investing in woke companies (Brammer et al., 2006) or that investors require a higher premium to compensate for the additional risk of investing in the least woke companies (Hong & Kacperczyk, 2009). For an investor, an equally weighted strategy may be easier to follow but as the returns are visibly lower than in the value-weighted portfolios, investors should invest in the value weighted portfolios.

6.4.3 Time divided performance of the portfolios

Our results from the time divided models indicate that the optimal strategy for obtaining the highest excess return in the two different value-weighted portfolio scenarios would be to invest in the top 15 and the top 50 portfolios in 2006-2012 and in the bottom 15 and top 50 portfolios from 2013 to

2019. In the first subperiod the highest excess return out of all portfolios is in the top 15 portfolio and for the second subperiod the bottom 15 has the highest excess return.

A sizeable part of the excess returns in the bottom 15 portfolio in the second subperiod can most likely be attributable to Facebook. Facebook and Berkshire Hathaway compose 28-35% of the weight in the bottom 15 portfolio and the weights of the companies are quite equally divided. The return of the S&P 500 was 126% during 2013-2019. Both companies outperformed the S&P 500 index during this period as the return of Berkshire Hathaway was +153% and the returns of Facebook increased by 659%. Facebook was listed in May 2012, hence the effect of the increase in returns is not present in the bottom 15 portfolio for 2006-2012. Even though the bottom portfolio overperforms the top portfolio according to the regression results, we can see from Figure 30 that the cumulative returns for the top 15 portfolio actually end up higher than the compounded returns of the bottom 15 portfolio, which might signal an increased interest in investing in socially responsible companies.

6.4.4 The relationship between wokeness and corporate financial performance

From our regression results, we can conclude that the relationship between wokeness and financial performance is not linear as the neutral portfolios have the lowest excess returns. One explanation is, that the number of companies included in the neutral portfolios is usually higher than the number of companies in the top and bottom portfolios and the excess returns show a tendency to decrease when the portfolio size increases. However, in the second scenario with the interval portfolios, all portfolios are of equal size and the excess returns of the neutral portfolios are still lower than the excess returns for the top and bottom portfolios.

This result supports that of Barnett and Salomon (2012), who discovered that the relationship between corporate social performance and financial performance is U-shaped. Firms with high corporate social performance outperform companies with low and moderate social performance and companies with low social performance outperform companies with moderate social performance. Our results indicate that this relationship seems to hold for wokeness too. The U-shape of the relationship suggests that investing in the wokest companies is the most profitable strategy due to the benefits of investing in ESG, such as reputation, are increasing more rapidly than the costs. As these companies also have the lowest amount of controversies, they do not suffer the costs of negative news. The neutral companies still invest in ESG but have not managed to make the benefits outweigh the costs. These companies are also affected by the cost of controversies which might explain the lowest excess returns. The least woke companies have lower ESG scores as they most likely do not invest much in their ESG strategy. These companies also have the most controversies and do not prioritize donations to democrats. This might signal that the companies follow the philosophy of Milton Friedman (1970) which is that companies should only care about increasing profits. This strategy could lead to higher excess returns for the least woke companies due to less investment costs in ESG when compared to the neutral companies. However, as these companies have the highest amount of controversies it might be one of the reasons for the inferior returns compared to the wokest companies as negative news decrease the market cap (Capelle-Balncard and Petit, 2019).

7 Conclusion

The aim of this thesis is to investigate how wokeness influences the financial performance of companies in the U.S. In this thesis high wokeness is defined as a combination of high ESG performance, a low amount of controversies, and corporate political donations mostly to the Democratic party. Companies are sorted into high, neutral, and low portfolios based on their wokeness scores. We find that companies with the highest wokeness scores are often donating mostly to the Democrats. In addition, the headquarters of these companies are usually situated in blue-leaning states. The wokeness scores are not consistent over time due to the impact of the Controversies score which fluctuates greatly. The financial performance of each portfolio is estimated using different multi-factor models.

The results of the empirical analysis suggest that all portfolios overperform the market in all examined periods. As the overperformance is more pronounced in 2006-2012 we suspect that there is a survivorship bias in the data that is causing the results as we exclude many companies from this period.

When comparing the financial performance of the value-weighted portfolios with one another, the results of the empirical analysis in the period 2006-2019 indicate that the relationship between wokeness and financial performance is U-shaped. The wokest and the least woke portfolios outperform the neutral portfolios and in most cases the wokest portfolio outperforms the least woke portfolio. However, the results lack statistical significance as the 95%-confidence intervals for the alphas clearly overlap one another. Our results suggest that an investment strategy where the portfolios are value-weighted is more profitable than investing in equally weighted portfolios. To follow an investment strategy based on high or low wokeness, investors need to rebalance their portfolios yearly as the wokeness score is not consistent over time.

Most previous literature has focused on the correlation between social performance and financial performance while less focus is put on the correlation between controversies and financial performance and corporate political donations and financial performance. Most previous literature has focused on the existence of the correlation while few focus on causality. Fulton et al. (2012) suggest that companies with high social performance have higher returns due to companies being foreseeing with environmental and social investments. Controversies tend to affect companies negatively due to loss of reputation and potential costs (Capelle-Blancard, 2019). Corporate political donations might affect financial returns either positively or negatively due to increased political influence or agency problems (Cooper et al., 2010 and Aggerwal et al., 2012). Our results suggest a positive correlation as the wokest companies mostly donate to the Democratic party.

7.1 Further research

We base our analysis on a wokeness index that we have created in an attempt to reproduce the results from the reference article. Hence, we do not consider adding other components than the ones from the article or adjusting the weights we assign to each component. One drawback of this approach is that we exclude other possible indicators of a company's wokeness, such as philanthropy. We suggest that future research investigates different means of wokeness. Furthermore, the weights we assign to each component is decided based on the weights used in the reference article. We suggest that future research experiment with different weights.

Another suggestion is to consider the amount companies donated to each party as our thesis does not differentiate between donation amounts. If a company donates $1000 to the Republicans and $1000 to the Democrats it is not likely to affect the financial performance, and further not likely to create an agency problem. On the other hand, if a company donates $500,000 solely to the Republicans, this could both yield a financial impact and represent a potential agency problem.

Our results suggest that industries perform differently in terms of wokeness, however, we do not control how different industries affect the financial performance. We suggest that future research should investigate if there is a link between the wokeness score, industry, and financial performance.

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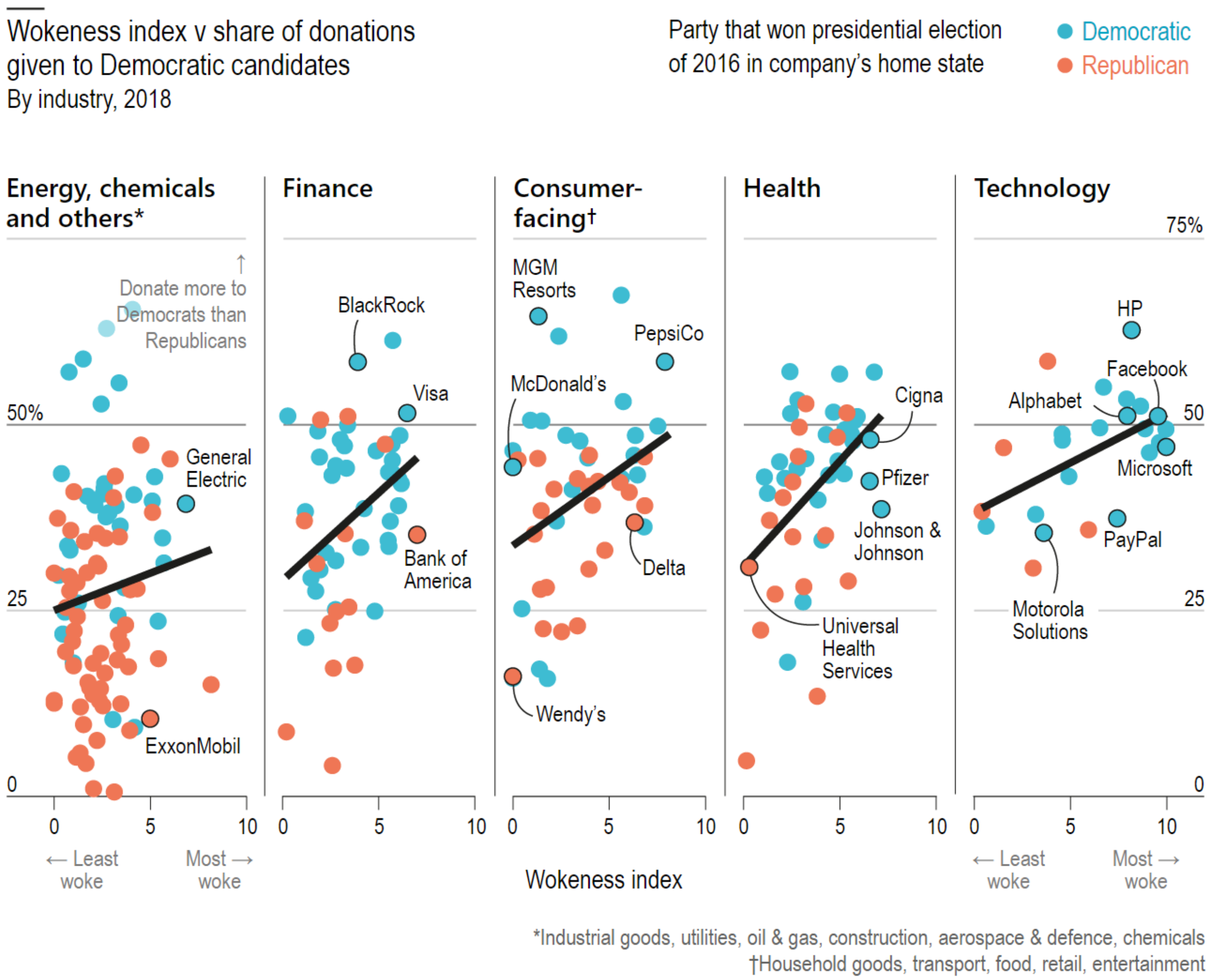
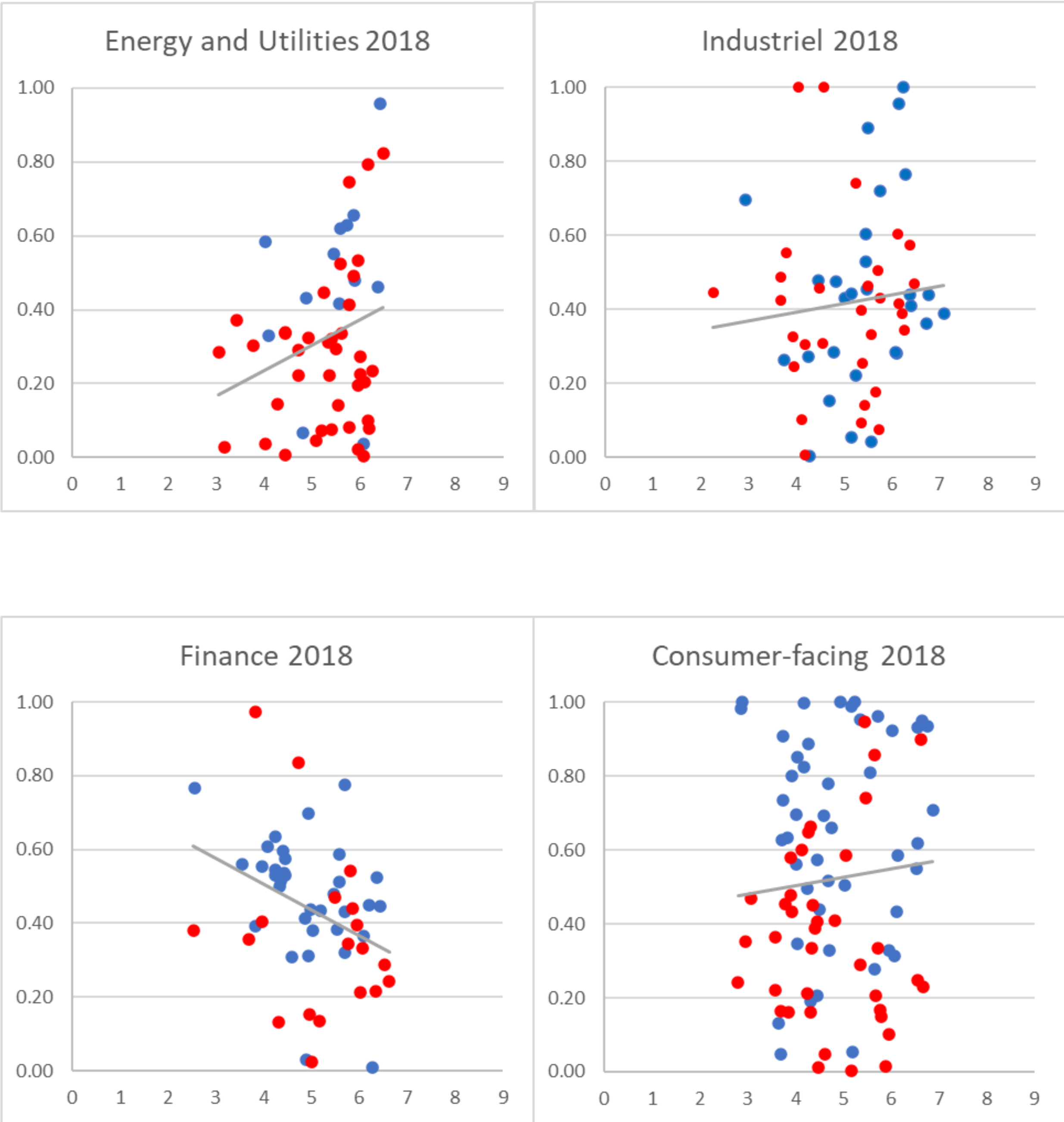
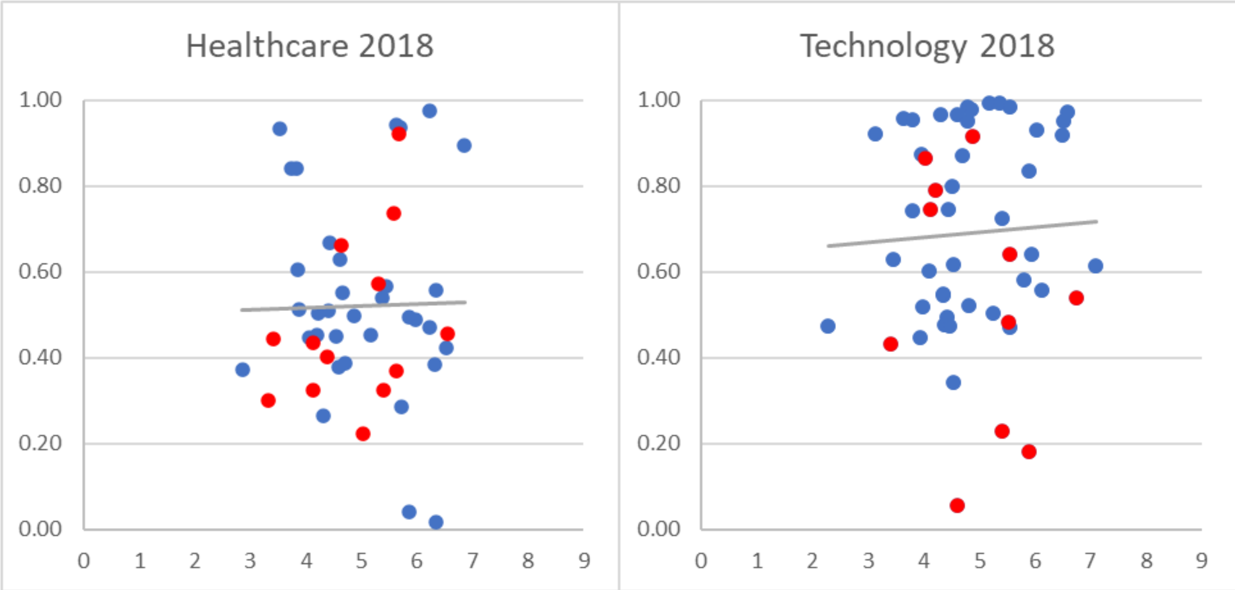
Appendix

Appendix 1: The graphs from the reference article (The Economist, 2019)



Appendix 2: wokeness score without political donation vs share of donations to the Democrats




Healthcare 2018
1.00
0.80
0.60
0.40
0.20
0.00
0
1
2
3
4
5
6
7
8
9
Technology 2018
1.00
0.80
0.60
0.40
0.20
0.00
0
1
2
3
4
5
6
7
8
9