ERASMUS UNIVERSITY ROTTERDAM

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SATISFIED EMPLOYEES, SATISFIED INVESTORS: IMPLICATIONS FOR QUALITY INVESTING

MASTER THESIS QUANTITATIVE FINANCE

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ABSTRACT

This paper links the stock return premium on high employee satisfaction to the quality factor. Firms with high levels of employee satisfaction attain abnormal stock returns, but, simultaneously, characteristics of high quality firms are often also found in firms with high levels of employee satisfaction. I hypothesize that there exists a link between the employee satisfaction premium and the quality premium. Firstly, I question whether employee satisfaction is providing a similar signal as the quality signal, but I find that the abnormal returns on stocks with high employee satisfaction are not attributable to the quality factor. Secondly, I test whether employee satisfaction may provide an additional signal for quality and I find that the quality factor can be improved by expanding it to include a measure of employee satisfaction. This analysis has implications for a better understanding of the quality factor, which has received a lot of attention from both, industry and academic researchers.

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1. INTRODUCTION

A rather fascinating indicator for abnormal stock returns is employee satisfaction. Yet, one may pose the question whether the positive relationship between employee satisfaction and long-run stock returns, found by Edmans (2011), is caused by a confounding influence. Intuitively, one would expect employee satisfaction to be related to firm quality. A high quality firm is typically a firm that is stable, profitable, and financially sound. It is also a firm with conservative management policy. Intuitively, these firms have the ability pay higher salaries and offer better employment conditions. They also have the means to make large human capital investments. Consequently, these activities would likely lead to higher contentment among employees. Therefore, higher employee satisfaction may be related to firm quality, a firm characteristic that has been confirmed to carry a return premium. Past evidence indicates that abnormal returns in excess of established factors value, size, and momentum can be realized through allocation on the basis of several separate accounting principles that identify strong and financially stable firms, i.e. high quality firms. Throughout this thesis, I propose that the quality of a firm is inherently interconnected to the attitude that its employees carry towards the firm, therefore, this link between employee satisfaction levels and asset prices can be used to enhance the quality factor.

In fact, the quality factor has recently received a great deal of attention in the academic literature and in the industry. Many have found a relationship between variables that indicate firm quality and returns, but a consensus on the best measures to identify firm quality, and thus the definition of the quality factor, has yet to be reached. Among others, Novy-Marx (2013) finds that stocks from more profitable firms earn higher returns, while Sloan (1996) documents a premium on low accruals. Recent literature proposes a combination of quality variables as a return predictor. For example, Piotroski (2000) finds that portfolios based on an aggregation of quality variables result in abnormal returns relative to a benchmark portfolio. Furthermore, Asness et al. (2015) and Kyosev (2013) construct a quality factor based on a combined measure of quality and verify its existence as a standalone factor, in addition to the size, value, and momentum factors. As the quality factor is a newly accepted factor, academics are still debating about the definition of quality and thus the contents of the quality factor. For instance, firm reputation, which Smith (2016) links to returns, could also be linked to quality.

Additionally, there is a lot of empirical evidence for other indicators or predictors for abnormal stock returns that might be related to quality. Employee satisfaction, which I focus on in this paper, is such an indicator. Edmans (2011) finds that stocks of companies on *Fortune*'s '100 Best Companies to Work For in America' outperform stocks of similar nature, but from companies not on the list. Additionally, portfolios formed from the stocks of the companies on these lists generate abnormal returns that are not explained by the market, value, size, and momentum factors. As an underlying explanation, Edmans posits that the stock market does not fully value intangible assets within a company. Therefore, when these intangibles lead to tangible benefits, the increase in stock prices follows only at a later stage, leading to superior returns. The author therefore links employee satisfaction to the social responsibility aspects of companies, thereby proposing that social responsible investing may improve investment returns. On the other hand, employee satisfaction as measured by this list may also, for example, be linked to employee pay as employees with higher salaries may regard their employer with higher contentment. Employee satisfaction may also have a relation to company profitability as more profitable firms are often able to offer better employment conditions (such as salary, good healthcare), as well as additional perks such as better office infrastructure and a more stimulating working environment, company trips/parties, gym availability, and even subsidized healthy lunch. A link between employee satisfaction and profitability, would then also suggest a relation with the quality factor because profitability has been identified by Kyosev (2013), Asness et al. (2015) and others as an important constituent of quality.

While employee satisfaction may indeed be standalone predictor, as suggested by Edmans' (2011) explanation of the employee satisfaction premium being a result the stock market's neglect of intangible value, this theoretical link between a firm's quality and its employee satisfaction remains of interest. The question that relics is how this link between the two firm characteristics translates to the effects of these characteristics on stock returns. Therefore, it is interesting to investigate the empirical link between the employee satisfaction premium and the quality factor. Employee satisfaction might provide a similar stock return signal as firm quality, and therefore the employee satisfaction premium that Edmans (2011) observes might, in fact, be this quality premium which has been documented by many. In that case, a quality factor will explain the employee satisfaction premium. Alternatively, employee satisfaction might provide an additional (disregarded) quality signal that should be incorporated into the still highly debated definition of the quality factor. The addition of an employee satisfaction dimension to quality might hence result in a quality factor that better explains stock returns than the existing quality factors. An empirical investigation of hypotheses is also very useful for the practical application of factor investing, as it is becoming common practice to allocate to factors at a strategic level in the asset allocation decision process. Hence, any enhancements of the quality factor are valuable to the industry as one may adapt quality factor allocations to the findings. To shed more light on the relationship between employee satisfaction and quality, I investigate the following research question:

'How is the employee satisfaction premium in stock returns related to the quality factor?'

In this research, I first confirm the earlier finding that employee satisfaction leads to higher stock returns and that such abnormal returns persist after accounting for the size, value, and momentum factors. For this I form portfolios of stocks based on the level of employee satisfaction of the stocks' firms. I use two measures for employee satisfaction. The first measure, as introduced by Edmans (2011), is based on the published lists of '100 Best Companies to Work for'. Using these lists, I form a portfolio of stocks of high employee satisfaction firms by including the stocks of the firms on this list. This allows me to investigate whether high employee satisfaction stocks attain abnormal returns in excess of known factors. I extend Edmans' (2011) US sample by also including the 'Best Companies to Work for' lists from Europe and Latin America and extending the sample period by six years.

I construct a second measure of employee satisfaction from the Corporate Sustainability Assessment (CSA) scores of sustainability investment specialist RobecoSAM. Such scores are available over a wide range of stocks over different countries and industries. The CSA scores are crucially different from the first measure as the scores are assigned to firms over a wide range of employee satisfaction levels. Whereas the measure of the '100 Best Companies to Work for' only allows me to investigate whether good employee satisfaction is associated with abnormal returns, the scores also permit an examination of the entire relationship between employee satisfaction level and returns, including the question whether firms with lower employee satisfaction attain lower returns. Using these CSA scores, I form decile portfolios of stocks based on their CSA scores, ranked from low to high employee satisfaction, allowing me to assess whether there exists a monotonically increasing relationship between employee satisfaction and factor-adjusted returns. Using both measures, I confirm that there exist some abnormal factor-adjusted returns within portfolios of high employee satisfaction and evidence shows that this effect is more pronounced within European stocks. However, outperformance due to high employee satisfaction is more prevalent than underperformance due to low employee satisfaction and a linear relationship between stock returns and employee satisfaction is not observed.

Subsequently, I focus on the relation between the quality factor and employee satisfaction and I conclude that the superior factor-adjusted returns due to employee satisfaction strategies are not attributable to the quality factor under its current definition. Taking that into account, I investigate whether the five-factor model (including the market, size, value, momentum, and quality factors) can be augmented by an employee satisfaction factor. I find that such a six-factor model does not have more explanatory power for individual stock returns than the five-factor model. Thus, employee satisfaction should not be considered as a standalone factor. This does not eliminate the possibility of employee satisfaction being able to contribute to another factor. Therefore, I consider employee satisfaction as an augmentation of the quality factor, thereby constructing a quality-plus factor. I find that a five-factor model which substitutes the quality-plus factor for the quality factor is better at explaining individual stock returns than the regular five-factor model with a more standard quality factor. Furthermore, I use the penalized Fama-MacBeth procedure to investigate the marginal effect of this quality-plus factor. I find that the marginal effect of the quality-plus factor, as well as that of its constituents, is meagre at the very best. However, neither the quality-plus factor nor its constituents are identified as irrelevant factors. Furthermore, Kleibergen and Zhan (2015)'s FACCHECK measure does not strongly indicate excessive unexplained factor structure in the residuals of the first step two-factor regression of the Fama-MacBeth procedure, thereby suggesting that the quality-plus factor captures some of the unobserved factor structure in stock returns that is not explained by the market factor. As evidence for abnormal returns on high employee satisfaction stocks is found, I conclude that there is a premium on employee satisfaction but that this effect does not hold across the board of employee satisfaction levels and is only relevant for the top employee satisfaction stocks. Furthermore, this effect can be used to improve the quality factor.

This paper proceeds with the literature review in section 2, followed by a description of the factor data that will be used in section 3. Section 4 then investigates the premium on the stocks from the '100 Best Companies to Work for', whereas section 5 investigates the relationship between employee satisfaction and stock returns using the CSA scores. Furthermore, section 6 investigates the possibility of an employee satisfaction factor and it also provides a first investigation into the employee satisfaction augmented quality-plus factor. Section 7 examines the performance of this quality-plus factor further and section 8 concludes.

2. LITERATURE REVIEW

Factor investing, a relatively new investment approach, utilizes strategies that allocate resources to factors known to earn returns in excess of the CAPM based explanation. Rather than picking single stocks that one expects to do well in the future, factor investing entails making a choice about desired factor exposure in a portfolio already at the strategic allocation stage. Established and widely accepted factors include the size and value factors of Fama and French (1992), the momentum factor of Jegadeesh and Titman (1993), and the low-volatility factor based on the low-volatility anomaly as in Jensen, Black and Scholes (1972). Recently, a new factor has been introduced in the academic literature: the quality factor. Freshly introduced and thus subject to scrutiny, academics are still debating about the existence and the definition of this factor.

Graham (1973) first proposed that stock picking based on fundamental measures results in outperformance in the long run. He defines quality on the basis of seven characteristics: 1) Adequate size of the firm, 2) Strong financial condition, 3) Stable earnings, 4) Good dividend history, 5) Earnings growth, 6) Moderate price/earnings ratio and, 7) Moderate price/assets ratio. Sloan (1996) digs into the earnings characteristic in this list of fundamental measures and finds that stock prices do not fully reflect the information contained within current earnings, thereby finding an inconsistency with the efficient market hypothesis, which states that stock prices reflect all public information. The author identifies accruals and cash flows as earnings components that have different properties with regards to their relation to future earnings, and thus the relative amount of the two components in earnings has different implications for stock returns. Namely, he finds that companies with lower accruals attain higher future earnings, a feat that is not incorporated in current stock prices and manifests in its returns when these future earnings are announced. Sloan's publication subsequently triggered a lot of academic interest in this accrual anomaly. For instance, Francis et al. (2005) propose accruals' quality as a separate priced risk factor. Next to the accruals, the relationship between returns and other accounting variables has also been thoroughly investigated. For instance, Novy-Marx (2013) finds that, ceteris paribus, stocks from more profitable firms earn significantly higher returns than those of unprofitable firms. Similarly, Fama and French (2006) find that when using lagged profitability, asset growth and accruals as proxies for expected profitability, more profitable firms have higher expected returns. Furthermore, Penman, Richardson, and Tuna (2007), as well as George and Hwang (2010), find that leverage is negatively associated with returns. Additionally, Pontiff and Woodgate (2008), McLean et al. (2009) find evidence of the cross-sectional predictability of stock returns by share issuance.

Taking into account the fact that Graham's (1973) definition of quality has many dimensions and the above evidence for accounting and fundamental variables' association with stock returns, it would appear of scientific relevance to investigate whether quality can be found in a combination of quality characteristics. A lot of research has indeed been done on this subject. For example, Piotroski (2000) finds that a strategy based on an aggregation of 9 quality variables, which include variables such as efficiency and profitability, can render abnormal returns relative to a benchmark portfolio. Also, Asness et al. (2015) define a quality security as a security that an investor should be willing to pay a higher price for and base their definition of quality on Gordon's growth model. Their quality measure consists of an average over four separate characteristics: profitability, profit growth, safety, and profit payout ratio. Each of these separate characteristics is proxied by several different measures, where the safety measure includes both return-based proxies and accounting proxies. These proxies are then transformed to a z-score before being averaged out to obtain a measure for each of the characteristics. The authors find that higher quality is associated with higher prices and construct a quality-minus-junk factor which goes long in quality (high quality) stocks and short in junk (low quality) stocks. This portfolio is found to deliver significant factor-adjusted returns and even has negative market, size and value exposures. Asness et al. (2015) judge that a simultaneous association of higher price and higher returns with higher quality need not be contradictory. The authors assign this observation to the possibility of mispricing still being present even in the presence of higher prices for quality, but do not adhere to a risk-based explanation because high quality stocks do not seem to have higher risk than junk stocks. In fact, high quality stocks even tend to do well during market distress periods.

Furthermore, Kyosev (2013) also defines the quality measure as a combined measure of several characteristics. These are gross profit to assets, accruals and free cash flows-to-assets. In this paper, I will stick to this definition of quality. The author verifies the existence of the quality factor (under his definition) as a standalone phenomenon and demonstrates that a long-short portfolio of high minus low quality stocks can earn an annual return of 15.72%. Therefore, although there still exists dispute about the content and form of the quality factor, its existence is definitely a fact. As a matter of fact, Frazzini et al. (2013) find evidence that much of Warren Buffet's (a great follower of Benjamin Graham) success with stock returns may be attributed to the quality factor.

In addition, one may argue a connection between firm quality and firm reputation. High quality may lead to improved reputation of a company, or vice versa. Actually, Smith (2016) constructs a portfolio consisting of stocks identified by *Fortune 100* magazine as America's 10 most admired companies, hence firms with good reputations, and finds that this portfolio outperforms the market benchmark. Furthermore, firms are nowadays increasingly faced with expectations by the public to incorporate social concerns into their daily activities, as well as make their business practices as sustainable and environmentally-friendly as possible. Firm reputation thus depends on the sustainability of its undertakings. As such, social corporate responsibility or sustainability has become an integral part of doing business. Subsequently, an important question is the effect of this trend on a firm's performance and thus indirectly, the effect on a firm's quality. Previous research has documented a positive link between such sustainable practices and performance. For example, Waddock and Graves (1997) and Preston and O'Bannon (1997) find a positive association between corporate social performance and financial performance. In addition, Verschoor and Murphy (2002) compare the ranking of firms on *Business Ethics magazine*'s '100 Best Corporate Citizens' list to *Business Week*'s financial performance rankings and find that the best corporate citizens ranked higher on the *Business Week* rankings, thus indicating that they were more profitable. Furthermore, Gillan et al. (2011) find a tendency of operating performance, efficiency, and firm value to increase with environmental, social, and governance (ESG) activities.

Related to an increase in firm value with ESG practices, an interesting question to raise is whether a firm's engagement in ESG activities positively affects its stock returns. In fact, Kempf and Osthoff build a long-short portfolio that goes long in stocks with high ratings of social responsibility and short in stocks with low ratings of social responsibility and find that such a portfolio actually achieves a four-factor alpha of up to 8.7% annually. On the other hand, one may also question whether such an effect would be due to the incorporation of social corporate responsibility in the firm's daily procedures and therefore indicates a premium on ESG stocks, or whether the stock market reacts to a firm's image. The latter is related to another rising trend, namely that of social responsible investing (SRI) in which investors take into account a firm's ESG concerns when picking stocks that they want to invest in. In fact, Hong and Kacperzyk (2009) actually even find that when there exists a societal norm against the operations of certain companies, for example tobacco companies, stocks of these companies attain higher expected returns than otherwise comparable stocks. The authors explain this occurrence by neglect of these stocks by norm-constrained (SRI) investors.

Employee satisfaction is, among others like environmental issues, an essential aspect of social corporate responsibility or sustainability. This is also the dimension of ESG that I want to focus on in this thesis. In previous research, Manescu (2010) finds that firms with better employee relations have higher expected stock returns than firms with inferior employee relations. Furthermore, Edmans (2011) finds similar results in his study of the relationship between employee satisfaction and long-run stock returns. The author finds a positive correlation between employee satisfaction and shareholder returns. In fact, defining a portfolio of high level of employee satisfaction as a portfolio of the stocks of the companies on *Fortune*'s '100 Best Companies to Work for in America', Edmans (2011) finds that such a portfolio earns a significant alpha in excess of the market, value, size, and momentum factors and that these stocks outperformed those of a similar nature but not on the '100 Best Companies to Work for in America' list. He attributes his results to the stock market not fully valuing intangibles in the sense that improved employee satisfaction causes superior firm performance, but the tangible outcomes of improved employee satisfaction, such as new patents, only manifest at a later point in time and are not incorporated in the stock price before. Further research into the '100 Best Companies to Work for' by Edmans et al (2014) shows that returns to list inclusion is not anomalous across countries but that an employee satisfaction premium is especially present in countries with more flexible labour markets.

Still, the question remains whether this effect may not be attributable to another factor. A simultaneous link between employee satisfaction and firm reputation and firm reputation and firm quality might suggest a relationship between this employee satisfaction premium and the quality factor. Additionally, many of the firms on such a '100 Best Companies to Work for' list are financially sound, stable firms that would likely also rank high on quality. Profitable firms are high quality firms and these are the firms that can offer better employment conditions, both in terms of salary as in terms of soft benefits such as better working equipment, and office infrastructure. Therefore, measures of employee satisfaction and of quality might be signaling the same effect on stock returns. In this paper, I build upon Edmans' (2011) research by linking his result to factor investing, and in particular finding its connection to the quality factor. One possible connection is that the employee satisfaction premium is explained by the quality factor in the sense that high employee satisfaction may be caused by the firm's quality; hence a premium on stocks from firms with high employee satisfaction will actually be the quality premium. An answer to this hypothesis contributes to the literature about the effect of ESG practices on stock returns, particularly to the literature linking employee satisfaction and stock returns, by investigating a possible underlying explanation for the employee satisfaction premium. On the other hand, it might be the case that employee satisfaction carries an additional quality signal for stock returns that differs from the signal of quality under its current definition. As mentioned previously, the definition of the quality factor is still being debated in academia. Therefore, it might even be the case that employee satisfaction or even reputational advantages were disregarded aspects of the quality factor. The addition of an employee satisfaction dimension to quality might hence result in a quality factor that better explains stock returns than the original quality factor. Therefore, this research is valuable for the understanding of the quality factor and it thereby contributes to the vast asset-pricing literature on factor models. Furthermore, such an employee-satisfaction enhanced quality factor might thus outperform the original quality factor. Such an enhancement of the quality factor is relevant for the industry as allocations to the quality factor might be improved, generating higher returns on quality strategies.

3. FACTOR DATA

This section discusses the factor data that is used to relate the employee satisfaction premium to known factors. The details on the construction and content of the two employee satisfaction measures used are extensively discussed in sections 4 and 5. In sections 4 and 5, I also discuss the universes of individual stocks that are used (the stocks of the companies on the lists of 'Best Companies to Work for' for the first part of the analysis and the stocks for which CSA scores exist for the second part of the analysis).

In addition to the data on specific stocks I will also use some known factors in this analysis. These known factors are the market factor, the value (HML) factor, the size (SMB) factor, the momentum factor, and the quality factor. I obtain monthly returns on the market, value, size, and momentum factors from the website of Kenneth French. For the analysis based on the 'Best Companies to Work for' lists, I make use of the US factors for the period of 1998-2015, the European factors of 2003-2015, and the global factors of 2003-2015. For the analysis based on the CSA scores I make use of the global, North-American, and European factors from 2003-2015. The corresponding risk-free rates are also downloaded from this website. These factors have been constructed using the Bloomberg database of April 2016. I perform the analysis from the point of view of a US-based investor. Therefore, all (factor and stock) returns are considered in dollar terms and the risk-free rate is the one-month return on a US T-Bill, which French obtained from Ibbotson and Associates Inc.

Further on in the research, I would like to adjust the quality factor; hence I need a quality factor that I am able to construct myself and to which I can make adaptions. Kyosev's (2013) quality factor suits this purpose. For my analysis of the CSA employee satisfaction measure, I construct the quality factor over the CSA universe. I first construct the quality score, according to the definition of Kyosev (2013), as an average of the z-scores of gross profit to assets, (negative) accruals and free cash flows to assets. Following this, the stocks are first sorted into two size portfolios according to their market capitalizations and then within these size portfolios they are sorted into terciles according to the firm's quality score. Subsequently, I construct the quality factor as follows:

$$Q = \frac{1}{2}(Small\ High\ Quality - Small\ Low\ Quality) + \frac{1}{2}(Big\ High\ Quality - Big\ Low\ Quality) \tag{1}$$

where small/big indicates the bottom/top size portfolio and low/high quality indicates the bottom/top quality tercile portfolios. Monthly returns on the quality factor are obtained by combining the value-weighted returns on the double sorted size-quality portfolios in the manner that is outlined in equation 1.

For my analysis regarding the lists of '100 Best Companies to Work for', I do not have a large enough universe to construct a corresponding quality factor out of it. The lists contain many non-publicly quoted firms (the amount depends on the region under consideration). This results in an amount of stocks that is not very representative to be divided over the six size-quality portfolios. Additionally, the '100 Best Companies to Work for' sample only includes high employee satisfaction stocks. Construction of a quality factor out of this sample will thus lead to a biased quality factor as compared to other quality factors that are constructed out of large universes that do not only consist of stocks that score high on a particular firm or stock characteristic but stocks over a large range of levels for all these characteristics. This bias will be especially large if the employee satisfaction signal for stock returns is proven to be related to the quality signal. Furthermore, I also do not have access to the quality constituents for the Fama and French universe. Therefore, I proxy Kyosev's (2013) quality factor by the quality-minus-junk (QMJ) factor of Asness et al. (2015). This factor is constructed on the basis of a quality measure that consists of a combination over four separate characteristics: profitability, profit growth, safety, and profit payout ratio. Each of these four separate characteristics is proxied by several different measures. These proxies are then transformed to a z-score before being averaged out to obtain a measure for each of the characteristics, which are in turn transformed to a z-score. The z-score of the sum of the characteristics z-scores then provides the quality measure. To construct the QMJ factor, Asness et al. (2015) first obtain six value-weighted portfolios by double sorting on size and on their quality measure. That is, they first sort stocks into two size portfolios and sort stocks into quality terciles within each of the two size portfolios. The QMJ factor is then constructed as demonstrated in equation 1. Monthly return data on this QMJ factor is available from the Applied Quantitative Research (AQR) website. I consider the US QMJ factor for the period of 1998-2015, the European QMJ factor for the period of 2003-2015, and the global QMJ factor for the period of 2003-2015.

The main difference between Kyosev's (2013) factor and the QMJ factor is that the QMJ factor includes the safety characteristic. The standard quality definition, and subsequently the quality factor, that I use in this paper is that of Kyosev (2013). I do this for two reasons. Firstly, due to its inclusion safety characteristic the QMJ factor overlaps with the low-volatility premium that was documented, among others, by Blitz and van Vliet (2007). Secondly, the quality measure of the QMJ factor of Asness et al (2015) is constructed out of 21 separate variables. I do not have access to observations on all these variables, hence I cannot recalculate the QMJ returns for my own universe, nor can I make adaptions to the QMJ factor while one of the main contributions of this paper is the construction of an improved quality factor that also considers an employee satisfaction measure next to its usual constituents. The quality factor considered in this paper does allow adaptions to include an employee satisfaction measure. Therefore, the only point at which I consider the QMJ factor in my empirical analysis is when I am considering the 'Best Companies to Work for' sample for which my universe is too small to construct my own quality factor out of. The widely established QMJ factor, which is constructed on a universe similar to that of the other factors obtained from Kenneth French's website, thus serves as an appropriate quality proxy for that part of the investigation. In fact, Pearson's correlation coefficient between the global QMJ factor and the global quality factor is 0.63; these values are 0.52 and 0.63 for the US and European samples, respectively. Therefore, even with these factors having different definitions and being constructed on different universes, these two factors still signal a similar quality effect.

4. BUY THE BEST COMPANIES TO WORK FOR

1. DATA AND PORTFOLIO FORMATION

In his paper about the relationship between employee satisfaction and stock returns, Edmans (2011) performs his analysis on stocks of companies on *Fortune 100*'s list of the'100 Best Companies to Work for in America'. The author uses the lists of 1984, 1993, and 1998-2005. The first two lists were published in books: the 1984 edition of 'The 100 Best Companies to Work for in America' book by Levering, Moskowitz, and Katz and the 1993 edition of the same-titled book by Levering and Moskowitz. The remaining lists were published in *Fortune 100* magazine. Edmans (2011) finds similar results of out-performance of the stocks of the companies on the list when excluding the first two lists; therefore I will consider data from 1998 onwards. I retrieve the lists from the 'Great Place to Work' website, which is also the source of the lists in *Fortune 100* magazine. In fact, I have lists of 1998-2016 for the best companies to work for in the United States. I ignore the 2016 list as little time has passed to evaluate the effect of the list on subsequent returns. I also expand the sample to the lists of best companies to work for in Europe and in Latin America. From the website these lists are available from 2003 until 2015 and 2004 until 2015, respectively. It is worthwhile to note that firms can apply to have their workplace quality evaluated by Great Place to Work and that the lists are based on the results of surveys among employees of applicant firms.

I should note that there are some small differences between the US lists and the lists from Europe and Latin America. Firstly, the latter two are not published in *Fortune 100* Magazine, whereas the US list is. Secondly, whereas for the US, there exists one list of '100 Best Companies to Work for' over time, the Latin American and European list set-up changes over time from '100 Best Companies to Work for' to a split of '50 Best Small and Medium-Sized Workplaces', '25 Best Multinational Workplaces' and '25 Best Large Workplaces'. I consider all three lists as indicators of high levels of employee satisfaction. One should note that the lists of best companies to work for also include privately held companies, as well as non-profit and governmental organizations. As I am investigating the effect of list inclusion on stock returns, I reduce my sample to only include those companies that are publicly listed in the year after the list publication, while I link list inclusion of a subsidiary to the returns of its parent company. In the case of European and Latin American lists, this reduces the sample significantly as a lot more companies on those lists are not publicly traded. Additionally, the European and Latin American lists also contain companies with stocks that are not listed on European or Latin American exchanges, but that are listed on other exchanges, as well as stocks listed on more than one exchange. In such cases, I always give priority to the stock listed on the exchange equivalent to the region of the list under consideration. If this stock is nonexistent, I take the stock from the other exchange.

For each year of list publication, I form a portfolio of the stocks of the firms on the lists at the end of March and hold this portfolio up to and including March the next year. I choose March as the formation period as all three lists are always published before the end of this month. Monthly returns on these portfolios are thus available from April until March every year, at the end of which the portfolio is reformed. Although the portfolio is formed yearly, I weigh the returns according to the stock's monthly market capitalization in the value-weighted portfolios. As Fama and French (2008) already prove that anomalies are not always robust over different weighting practices, I form both equal-weighted and value-weighted portfolios in the manner of Edmans (2011). As mentioned previously, the European and Latin American lists do not only contain companies whose stocks are listed on European and Latin American exchanges. In addition to forming a region portfolio of all stocks on each of the regional lists, I also form separate portfolios of only the stocks that are traded on exchanges in the same region as the 'Best Companies to Work for' list under consideration. These are the 'home' portfolios. The remaining stocks on the lists are then gathered in alternative 'foreign' portfolios. I also form a complete 'Full Sample' portfolio which includes stocks from the three lists combined.

Additionally, the portfolios will be benchmarked against factors. One should take caution with the (regional) universe that is used to construct these factors. For the Full Sample, Europe, and Latin-America portfolios, I make use of global factors as these portfolios contain stocks that are traded on exchanges in different regions. For the Europe-Home portfolio I take the European factors, while US factors are used in the analysis of the US and the Europe-Foreign portfolios as the Europe-Foreign portfolio only includes US traded stocks. Lastly, the Latin-Foreign portfolio is also benchmarked against the global factors as this portfolio includes Europe and US traded stocks. The number of stocks in this portfolio is too small to warrant another split into smaller portfolios based on exchange location.

Table 1 indicates the regional portfolios that I form, as well as the regions where the exchanges, that its constituent stocks are traded on, are located. It also includes the regions of the benchmark factors that are considered for each portfolio.

TABLE 1

Definition of Regional Portfolios

This table shows an overview of how the regional list portfolios are defined. It shows the region for which the portfolio constituents appear on the '100 Best Companies to Work for' list. It also shows region of the exchanges on which the portfolio constituent stocks are traded. Also, the portfolios are benchmarked against the Fama and French factors and the QMJ factor, which are calculated over regional universes. The last column shows the appropriate region for the benchmark factors for these portfolios.

Portfolio	List Region	Stock Exchange Region	Factor Region
Full Sample	US, Europe, Latin America	US, Europe, Latin America	Global
Europe	Europe	US, Europe	Global
Europe-Home	Europe	Europe	Europe
Europe-Foreign	Europe	US	US
US	US	US	US
Latin America	Latin America	US, Europe, Latin America	Global
Latin-Home	Latin America	Latin America	Latin America
Latin-Foreign	Latin America	US, Europe	Global

Table 2 shows an overview of the number of publicly quoted firms on the lists of '100 Best Companies to Work for', i.e. the number of stocks included in the portfolios. Note that as the Full Sample portfolio consists of an aggregation of the companies on the European, US, and Latin American lists, I only consider the lists from 2004-2015 for this portfolio because these are the years for which lists from all three regions are available.

TABLE 2

Number of Stocks in List Portfolios

This table shows an overview of the number of stocks in each of the list portfolios. Firms on the '100 Companies to Work for' lists were obtained from the 'Great Place to Work' website. The stocks of the firms on these lists that are publicly quoted in the year after the list publication are included in the corresponding portfolios. List inclusion of a subsidiary firm is linked to the stock of its parent company. The time period in column 2 shows the years for which 'Best Companies to Work for' lists were available at the time of investigation. Portfolios are formed at the end of March of the year of list publication and held up to and including March the next year. The last portfolio returns are thus available for March 2016 as end of March 2015 is the last point of portfolio formation. Turnover is defined as the average between the number of firms that newly occur on the list and the number of firms that disappear from the list.

Portfolio	List Time Period	Total number firms over Time	Average firms over Time	Median firms over Time	Average Turnover over Time
Full Sample	2004-2015	293	97	99	25
Europe	2003-2015	114	29	30	11
Europe-Home	2003-2015	36	8	8	3
Europe-Foreign	2003-2015	78	21	22	7
US	1998-2015	194	52	49	11
Latin America	2004-2015	64	20	20	6
Latin-Home	2004-2015	23	7	7	2
Latin-Foreign	2004-2015	41	13	14	3

The full sample consists of 374 stocks of the firms on the US, Europe, and Latin America list over the period of 1998 until 2015. Restricting the sample to the period of 2004 until 2015, this results in 293 different stocks in the Full Sample portfolio over time. This leads to an average of 97 constituent stocks for the Full Sample portfolio over the period of 2004 until 2015 with, on average, 25 changes in portfolio constituents per year. The US lists accounts for the largest part of these stocks, followed by the European lists while the amount of publicly listed firms on the Latin America lists is much smaller. Previous discussion indicated that the European and Latin-American lists contain more non-profit, governmental, and private organizations and companies than the US lists and one may observe indeed that while, on average, about 50 of the 100 companies on the US list are traded the year after list publication, this number is much lower for the European and Latin American lists. This also indicates that portfolios based on these lists, especially those that have been split according to exchange location, will be poorly diversified. For this reason, I disregard the Latin-Home portfolio because for this portfolio the amount of stocks that would be included is very small. In fact, for some years there would not be any portfolio to form, as it would be empty. Additionally, the sample periods for the Full Sample, European and Latin America portfolios contain 12 and 13 years of lists, a similar amount to the 11 years of lists Edmans (2011) uses in his US sample from 1998 until 2009. For the US, I have 17 years of lists, which appears to be ample. I hence extend Edmans' (2011) US sample by 6 years and consider additional regions to the sample that he considers. Edmans et al (2014) also look into the 'Best Companies to Work for' from countries other than the US, but I focus on regions here.

To form portfolios based on employee satisfaction, I require monthly observations on returns and market capitalizations for the list companies. Edmans (2011) uses CRSP data, while I obtain these variables corresponding to these stocks on the lists of '100 Best Companies to Work for' from FactSet. I consider a total returns measure that includes dividends and consider all variables in dollar terms. Returns are denoted in percentage terms. I also obtain observations on book-to-price ratios in order to be able to get a sense of the types of stocks that are contained within these lists.

Yearly descriptive statistics of these characteristics of the stocks in these 'Best Companies to Work for' portfolios can be found in Tables A1-A3 in the appendix. The descriptive statistics for returns are calculated once a year at the end of March of the year after list publication, as this is the last month for which one may link returns to a '100 Best Companies to Work for' list. Descriptive statistics for the market capitalization and book-to-price ratios are calculated at the end of March in the year of portfolio construction. One can observe quite some variation in the returns between regions in Table A1. These are all high employee satisfaction stocks, hence the employee satisfaction premium might differ between regions. From the descriptive statistics regarding market capitalization in Table A2, one can observe that generally the stocks of the firms on the different region lists have market capitalizations of the same order of magnitude. This entails that should there be large differences in performance of list stocks between regions, this unlikely to be due to the size factor. The same holds for regional performance differences with regards to the value factor as can be seen in Table A3. Although there is quite some variation in the book-to-price ratios over time, they do not differ so much in order of magnitude between different region lists at the same point in time. This suggests that any performance differences between regional list stocks are likely not explained by the value factor.

2. METHODOLOGY: FACTOR REGRESSIONS

A first aim in this paper is to investigate whether stocks of firms with high employee satisfaction achieve abnormal returns in excess of the known factor premiums. When one wants to examine whether a certain firm characteristic leads to abnormal returns, this is often done by regressing the excess returns of portfolios that are formed on the basis of this firm characteristic on these known factors. Any abnormal returns in the portfolios that are not attributable to the portfolios' factor exposures will then be collected in the intercept (alpha) of the coefficient estimates of the regressions. I regress the portfolio returns of these portfolios of companies on the '100 Best Companies to Work for' lists on the one-factor (CAPM) model, Carhart's (1997) four-factor model, and a five-factor model that augments Carhart's (1997) four-factor model with the quality-minus-junk factor. I use the QMJ factor as a proxy for Kyosev's (2013) quality factor, which, as mentioned previously, I consider as the standard quality factor in this research. These models can be expressed as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{MKT,i}\,(R_{MKT,t} - R_{f,t}) + \varepsilon_{it,1} \tag{2}$$

$$R_{it} - R_{f,t} = \alpha_i + \beta_{MKT,i}\,(R_{MKT,t} - R_{ft}) + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}MOM_t + \varepsilon_{it,2} \tag{3}$$

$$R_{it} - R_{f,t} = \alpha_i + \beta_{MKT,i}\,(R_{MKT,t} - R_{ft}) + \beta_{SMB,i}SMB_t + \beta_{HML,i}HML_t + \beta_{MOM,i}MOM_t + \beta_{QMJ,i}QMJ_t + \varepsilon_{it,3} \tag{4}$$

with the assumption that $\varepsilon_{it,j} \sim NID(0, \sigma^2_{\varepsilon,j})$ for $j = 1,2,3$. Here, $R_{it} - R_{f,t}$ is the excess return on portfolio i at time t. Excess returns are monthly returns on the portfolio in excess of the risk-free rate which is proxied by the one-month US T-bill rate. Furthermore, α_i is the intercept, capturing the abnormal returns adjusted for factor exposure and $(R_{MKT,t} -$

$R_{f,t}$) is the excess return on the market portfolio, while SMB_t, HML_t, MOM_t, and QMJ_t are the returns on the value, size, momentum, and quality-minus-junk factors. If an alpha that is significantly different from zero results from regressions 2, 3 and, 4 this then indicates outperformance that does not simply result from factor exposure to the respective factors in the regressions. Since the '100 Best Companies to Work for' portfolio is a stand-alone portfolio that will not be compared to other portfolios, it is plausible to use a t-test to test for the significance of the alphas.

By performing the regression in equation 2, I can investigate whether superior employee satisfaction is indeed accompanied with higher returns. The regression in equation 3 can be used to examine whether this effect can be explained by the value, size, and momentum factors. The addition of the QMJ factor in equation 4 then further indicates whether a possible return premium due to higher employee satisfaction can attributed to the quality factor. Should the addition of the QMJ factor subsume the return premium, one can further investigate whether a firm with high employee satisfaction does not add value in terms of investment choice when quality factor allocation is already being used.

3. Empirical Evidence for an Employee Satisfaction Premium

In this section, I discuss the results of the portfolios of the stocks of the companies on the '100 Best Companies to Work for' lists. Table 3 shows the performance measures and the results of the factor regressions (outlined in equations 2, 3, and 4) of the equal-weighted portfolios. For each of the regressions, I test for heteroscedasticity and serial correlation in the error term, ε_{it}, using the Breusch-Pagan and Ljung-Box Q tests, respectively. In the case that either is found to be present at the 5% significance level, I make use of Newey-West standard errors.

Panel A shows the performance measures of the portfolios of the stocks of the companies on the '100 Best Companies to Work for' lists. These measures are calculated on a monthly basis and then annualized. One may notice that the Europe-Home portfolio has particularly high average excess returns, as well as Sharpe ratios. This is a first indication that European stocks of companies with high employee satisfaction do especially well. This might be because Europe has more strict labour conditions laws. Hence, the best companies to work for in Europe are the best companies within a sample of companies that already have very good labour conditions and thus the top levels of employee satisfaction are higher than the top levels of employee satisfaction in the other regions. This does not necessarily oppose the finding of Edmans et al. (2014) who find that the employee satisfaction premium is diminished in countries with inflexible labor markets. Good labour conditions does not necessarily mean that employees will not want to leave, especially if the labour conditions are just as good in other companies. The top employee satisfaction firms in Europe will still retain more of its employees and motivate them more than the other European firms, and this manifests in the stock returns. The Latin America portfolio also has a much higher Sharpe ratio than the other portfolios. The other portfolios are quite similar in their Sharpe ratios, as well as their average excess returns, with the exception of the Europe portfolio. The latter is likely attributable to the superior performance of the Europe-Home stocks that are also in the Europe portfolio. Furthermore, Panel B shows the regression results of the excess returns of the several regional portfolios regressed on the market factor and a constant. In the panel, the portfolios are organized in the columns while the first row shows the alpha estimates with the corresponding *t*-statistics in the brackets. The panel also shows the estimated coefficient on the market factor and the adjusted *R*-squared of the regression. One may observe that the equal-weighted portfolios deliver abnormal returns in excess of the market factor that are statistically significantly different from zero at least at the 5% significance level for most of the portfolios, except for Europe-Foreign and Latin-Foreign portfolio. The portfolios also outperform the market benchmark significantly in an economic sense, as they are realizing positive market-adjusted returns (alpha). One may also observe high significance on the market factor.

Panel C shows the corresponding results for regressions of these portfolios on the market, size, value, and momentum factors, as outlined in equation 3. The panel is structured in a similar manner as Panel A, but it also provides the coefficient estimates on the size, value, and momentum factors. One can observe that, in general, the factor-adjusted abnormal returns (alpha) differ significantly from zero, often even at the 1% significance level. Only the Europe-Foreign portfolio does not produce an alpha that differs statistically significantly from zero. On the other hand, since the remaining portfolios still produce abnormal returns after adjusting for factor exposure, it appears that stocks of firms with high employee satisfaction do in fact yield higher returns, and that this effect is not attributable to the size, value, or momentum factors.

Furthermore, Panel D shows the analogous results when the four-factor model is augmented by the QMJ factor. From Panels C and D, one may note that these portfolios generally load negatively on the value (HML) factor. This is unsurprising as (discussed in the data section) the stocks in the portfolio tend to have high price-to-book ratios, suggesting that these are generally growth stocks. Also, with the exception of the US portfolio which has a statistically significant positive coefficient for the size factor, these portfolios generally load negatively or neutrally on size. Therefore, the US portfolio must contain a lot more small caps than the other portfolios.

In addition, one may observe that the five-factor alphas are lower than those of the four-factor regressions, suggesting that the premiums that were found previously might in part be attributable to the quality factor. The Europe-Home, US, and Latin-America alphas remain statistically significant; this means that the quality factor cannot explain all the premium that is found on employee satisfaction. On the other hand, the five-factor alphas of the Full Sample, Europe, and Latin-Foreign portfolios lose their statistical significance as compared to their four-factor alphas. These portfolios generally load positively on the QMJ factor and in the case of the Full Sample and Latin-Foreign portfolios the QMJ coefficients differ significantly from zero at least at the 10% significance level. As the addition of the QMJ factor also eliminated the statistical significance of the alphas on these portfolios as compared to the four-factor alphas, one can conclude that

TABLE 3

Factor-Adjusted Returns of Equal-Weighted List Portfolios

This table shows the key performance measures and the regression results of equal-weighted portfolios formed out of the stocks of the firms on the '100 Best Companies to Work for' lists, as defined in Table 1. Portfolios are considered for the periods indicated in Table 2. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression, respectively. In these regressions, monthly excess returns of these equal-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. β_{Mkt}, β_{SMB}, β_{HML}, β_{MOM}, and β_{QMJ} are the regression coefficients on these factors. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. The last row of Panels B, C, and D reports the adjusted R-squared values of the regressions.

Panel A: Performance Measures							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	10.12	11.46	19.25	8.83	9.81	13.86	8.21
Volatility	15.94	16.72	18.31	17.94	18.96	15.91	14.71
Sharpe	0.63	0.69	1.05	0.49	0.52	0.87	0.56
Panel B: CAPM							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
α	0.31**	0.20*	0.80***	-0.06	0.32*	0.66***	0.22
	(2.09)	(1.72)	(5.13)	(-0.45)	(1.76)	(2.82)	(1.59)
β_{Mkt}	0.94***	0.94***	0.84***	1.01***	1.11***	0.81***	0.83***
Adj. R^2	0.86	0.76	0.78	0.66	0.89	0.64	0.79
Panel C: 4-Factor Regressions							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
α	0.41***	0.31**	0.88***	-0.03	0.33**	0.74***	0.28**
	(2.88)	(2.61)	(4.20)	(-0.23)	(2.16)	(3.15)	(2.21)
β_{Mkt}	0.90***	0.93***	0.86***	1.02***	1.05***	0.77***	0.83***
β_{SMB}	-0.09	-0.26***	-0.08	-0.14	0.18***	-0.17	-0.43***
β_{HML}	-0.05	-0.18	-0.21**	-0.15	0.02	0.19	-0.00
β_{MOM}	-0.17***	-0.11**	-0.09	-0.10**	-0.08***	-0.12***	-0.07
Adj. R^2	0.87	0.77	0.78	0.69	0.91	0.65	0.81
Panel D: 5-Factor Regressions (Includes QMJ Factor)							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
α	0.24	0.16	0.70***	-0.03	0.27*	0.53*	0.01
	(1.38)	(0.88)	(2.91)	(-0.20)	(1.96)	(1.88)	(0.05)
β_{Mkt}	0.99***	1.01***	0.91***	1.02***	1.09***	0.87***	0.96***
β_{SMB}	0.03	-0.16	0.01	-0.14	0.21***	-0.04	-0.26**
β_{HML}	0.00	-0.14	-0.08	-0.15	0.02	0.24	0.08
β_{MOM}	-0.20***	-0.14**	-0.14**	-0.10***	-0.09*	-0.16**	-0.11**
β_{QMJ}	0.25*	0.22	0.29	0.00	0.09	0.29	0.39***
Adj. R^2	0.87	0.77	0.78	0.67	0.91	0.65	0.82

the employee satisfaction premium on the Full Sample portfolio and the Latin-Foreign portfolio is attributable to the QMJ factor, yet this does not appear to be the case for the other portfolios.

Furthermore, it appears that an equal-weighted portfolio of those stocks of 'Best Companies to Work for', but listed on other exchanges do not show as large an employee satisfaction premium as the other portfolios. Namely, the Europe-

Foreign portfolio has a slightly negative alpha that is virtually equal to zero and thus that result also lacks economic significance next to statistical significance. In addition, the Latin-Foreign one-factor and five-factor alphas lack statistical significance. One possible explanation is that firms with stock listings in another region than their 'Best Companies to Work for' list inclusion likely also have headquarters in another region. This would suggest that a lot of the activities which might lead to higher stock returns due to employee satisfaction, such as research, will not take place in the region for which the firm appears on the list. Furthermore, these are likely large firms for which high employee satisfaction within one region does not necessarily indicate high employee satisfaction in the entire firm. Thus, firm employee satisfaction in a region that differs from the headquarters of the firm will not contribute as much to firm value as employee satisfaction in some more relevant regions. The latter occurrence is reflected in the firm's stock returns.

Table 4 shows the corresponding results for the factor regressions of the value-weighted portfolios. This table is constructed in a similar manner as Table 3. Additionally, considerations about the use of Newey-West standard errors remain the same as in Table 3. At a first glance, one may notice that the average excess returns are much higher for the equal-weighted portfolios than for the value-weighted portfolios. However, the Sharpe ratios of the two portfolio types are relatively similar due to the generally higher volatilities of the equal-weighted portfolio returns. Furthermore, although the alpha estimates from the value-weighted portfolios are generally positive for the CAPM and four-factor regressions and thus seem of economic importance, they are generally lower than those of the equal-weighted portfolios and most lack statistical significance, even at the 10% significance level. This suggests that a lot of the stocks in the portfolios may be small caps, attaining at least part of their abnormal returns from the size factor. Only the value-weighted Europe-Home and Latin-American portfolios produce alphas that differ significantly from zero. In addition, from Panels C and D, one can also observe that the loadings on the size factor are, as expected, negative and these coefficients differ significantly from zero at the 10% significance level and up. Re-call that the equal-weighted portfolios had either negative coefficients or coefficients that were virtually zero for the size factor. This change in size exposure is unsurprising when moving from equal-weighted to value-weighted portfolios. Moreover, these portfolios also generally have negative loadings that differ significantly from zero or loadings that are virtually zero on the value and momentum factor. These negative/zero loadings on these three well-known factors again suggest that the positive alphas have another source.

Furthermore, Panel D demonstrates that, similarly to the equal-weighted portfolios, the addition of the QMJ factor leads to reduced alphas. However, with the exception of the Europe-Home portfolio, these alphas are negative but they do not differ significantly from zero. As these portfolios were already not significantly outperforming the four factors, this does not necessarily mean that these negative alphas are due to the QMJ factor. Yet, in the case of the Latin portfolios, the addition of the QMJ factor causes the loss of alpha significance. For those portfolios, the coefficients on the QMJ factor are positive and differ significantly from zero. QMJ coefficients are similar for the Full Sample, Europe, and Europe-Foreign portfolios. Therefore, the returns on these value-weighted portfolios are partially explicable by the QMJ factor.

TABLE 4

Factor-Adjusted Returns of Value-Weighted List Portfolios

This table shows the key performance measures and the regression results of value-weighted portfolios formed out of the stocks of the firms on the '100 Best Companies to Work for' lists, as defined in Table 1. Portfolios are considered for the periods indicated in Table 2. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression, respectively. In these regressions, monthly excess returns of these value-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. β_{Mkt}, β_{SMB}, β_{HML}, β_{MOM}, and β_{QMJ} are the regression coefficients on these factors. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. The last row of Panels B, C, and D reports the adjusted R-squared values of the regressions.

	Full sample	Europe	Europe-Home	Europe-Foreign	US	Latin America	Latin-Foreign
Panel A: Performance Measures							
Avg. Ret.	7.15	8.13	17.03	7.02	6.24	7.43	7.76
Volatility	14.66	13.89	16.98	13.99	19.86	14.88	14.76
Sharpe	0.49	0.58	1.00	0.50	0.31	0.50	0.53
Panel B: CAPM							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
α	0.13	0.07	0.73***	-0.07	0.05	0.18	0.22
	(0.84)	(0.41)	(3.26)	(-0.46)	(0.27)	(0.90)	(1.28)
β_{Mkt}	0.83***	0.78***	0.73***	0.84***	1.12***	0.78***	0.76***
Adj. R^2	0.80	0.76	0.68	0.76	0.82	0.68	0.65
Panel C: 4-Factor Regressions							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
α	0.19	0.17	0.68***	-0.06	0.16	0.23*	0.25*
	(1.28)	(1.14)	(3.11)	(-0.39)	(1.23)	(1.68)	(1.66)
β_{Mkt}	0.85***	0.80***	0.85***	0.93***	1.10***	0.80***	0.79***
β_{SMB}	-0.49***	-0.54***	-0.24**	-0.40***	-0.17***	-0.56***	-0.56***
β_{HML}	-0.15	-0.06	-0.46***	0.01	-0.35***	-0.11	-0.14
β_{MOM}	-0.06	-0.04	0.07	-0.03	-0.01	-0.04	-0.01
Adj. R^2	0.83	0.80	0.72	0.80	0.86	0.72	0.68
Panel D: 5-Factor Regressions (Includes QMJ Factor)							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
α	-0.12	-0.24	0.66***	-0.21	0.08	-0.16	-0.15
	(-0.74)	(-1.44)	(2.61)	(-1.40)	(0.64)	(-0.80)	(-0.69)
β_{Mkt}	1.00***	1.01***	0.85***	1.03***	1.14***	0.99***	0.99***
β_{SMB}	-0.28***	-0.25**	-0.23*	-0.33***	-0.12**	-0.31**	-0.30**
β_{HML}	-0.06	0.06	-0.44***	0.06	-0.36***	0.00	-0.03
β_{MOM}	-0.11**	-0.11**	0.06	-0.06*	-0.02	-0.10**	-0.07
β_{QMJ}	0.45***	0.61***	0.03	0.28***	0.12	0.56***	0.58***
Adj. R^2	0.84	0.82	0.72	0.82	0.86	0.73	0.70

It is interesting to examine the performance of the (equal-weighted and value-weighted) Europe-Home portfolios: these portfolios significantly outperform the four- factor benchmarks at the 1% significance levels and their estimated alphas are very high, on a monthly basis, as compared to the alphas of the other portfolios. This outperformance even remains in the presence of the QMJ factor: the alphas are high (0.70 for the equal-weighted portfolio 0.66 for the value-weighted portfolio) and differ significantly from zero at the 1% significance levels. It thus seems that an employee satisfaction premium is particularly prevalent in European stocks. This can again be explained by the strict labour condition laws in Europe resulting in the companies on the '100 Best Companies to Work for' having the best of the best working conditions. In addition, neither the equal-weighted nor the value-weighted portfolio have QMJ coefficients that differ significantly from zero. Hence, these superior returns of the Europe-Home portfolios do not appear to be attributable to quality.

Furthermore, when considering the US sample, I estimate positive factor-adjusted excess returns (even in excess of the QMJ factor) for both the equal-and value-weighted portfolios. This is an economically significant indication, yet, similar to Edmans' (2011) results for his smaller sample period, the equal-weighted alphas show strong statistical significance while the value-weighted alphas do not. Furthermore, the other value-weighted alphas were also smaller and often less significant than their value-weighted counterparts. I attribute this to the small amount of stocks present within the portfolios. The US portfolio consists, on average, of about 52 stocks. The other portfolios are even smaller. Therefore, when value-weighting the portfolios, one or a couple of large market cap stocks can really dominate the portfolio return series, whereas the equal-weighted portfolios give more weight to the small market cap stocks.

Lastly, I would also like to comment on the adjusted *R*-squared values that are reported in Tables 3 and 4. One may notice that the adjusted *R*-squared values of the four-factor regressions are only slightly higher than those of the CAPM regressions. Furthermore, the adjusted *R*-squared values of the four-and five-factor regressions are nearly identical. This suggests that the addition of the QMJ factor does not increase the explanatory power of the factor model (by more than would be expected by chance) for the portfolio returns considered here. This observation provides an additional indication that the QMJ factor cannot explain the (four-) factor-adjusted abnormal returns on these high employee satisfaction portfolios.

In the end, from Table 3 and 4 I conclude that there exists a premium on employee satisfaction, taking into account the statistically significant results regarding the equal-weighted portfolios and the economic interpretation of the alphas of the value-weighted portfolios. In case of the value-weighted portfolios, this result appears to be explained by the quality factor considered here, but this does not hold for the equal-weighted portfolios.

Now that I have established the existence of a premium on portfolios of the stocks on the '100 Best Companies to Work for' lists, it is also interesting to examine the performance of these portfolios over its holding period, that is from the moment of re-balancing in April until just before the portfolio is re-balanced again according to the new list the next year. Figures A1-A7 in Appendix A3 show the average per-month performance of the list portfolios. For each month, average returns are calculated over the sample period. Then the average cumulative compound excess returns of 1 dollar being invested in the portfolios at the end of March during an average year are calculated by compounding the average returns relative to the base month March. In general, these cumulative excess returns tend to increase over this average year, with a slight dip in January and February. This suggests that the employee satisfaction premium is not due to some publication effect with investors paying close attention to the firms on the list, and then buying these stocks thereby driving up their prices in the months closely following list publication. In fact, since growth in cumulative excess returns is also observed over the rest of the year, the employee satisfaction premium appears to be due to the intrinsic effect of employee satisfaction on firm performance and is not explicable by investor behavior in reaction to list publication. Focusing on the Europe-Home portfolios, the portfolios on which the largest employee satisfaction premium was observed, one can even notice that the growth of cumulative excess returns is strongest in the middle and at the end of the holding period, disregarding the publication effect explanation completely for these portfolios.

Furthermore, since the level of employee satisfaction is a firm characteristic that will not change instantaneously but rather remain around the same level and perhaps change gradually, it is also interesting to examine portfolios of stocks of the firms that are new arrivals to the '100 Best Companies to Work for' lists and portfolios of stocks of the firms that are delisted from the lists. This will allow me to distinguish whether the employee satisfaction premium is due to the intrinsic employee satisfaction value to the firm or due to list inclusion. At the end of March of each year, the new arrivals portfolios are constructed out of stocks which appear on the newest list but were not on the most recent list before that. Observations on these portfolios are only available from one year later than its original sample period. Tables A8 and A9 in Appendix A3 show the performance measures and regression results of the equal-and value-weighted new arrivals portfolios, respectively. The performance of these portfolios is much lower than that of the original portfolios that included all stocks from firms on the lists. This holds in terms of the annual average excess returns as well as in terms of the factor-adjusted returns (alphas). In fact, in the case of the equal-weighted portfolios the five-factors alphas are even negative, yet these alpha estimates are not statistically significant. In the case of the value-weighted portfolios, I estimate even some statistically significantly negative five-factor alphas and these alphas are also more negative than those of the original list portfolios. Since these are stocks of firms which have recently reached a higher level of employee satisfaction, this shows that the employee satisfaction premium might be a long-term effect and abnormal returns do not automatically follow list inclusion. In other words, it will take some time for the intangible firm value of employee satisfaction to manifest in the firm's stock returns. On the other hand, one may observe an even stronger employee satisfaction effect on the Europe-Home portfolios than the effect from the original portfolios, suggesting that either the European market reacts to list publication (but this seems rather unlikely as a quite monotonic increase in average cumulative portfolio returns was observed over the year in Figure A3) or European stock returns are related to the change in employee satisfaction level.

I now examine the results of the equal and value-weighted portfolios of stocks that disappear from the 'Best Companies to Work for' lists in Tables A10 and A11 in Appendix A3. These delisted portfolios are constructed out of those stocks that are not on the newest list but were on the most recent list before that. Observations on these portfolios are also only available from one year later than its original sample period. One may notice that the performance of these portfolios is lower than that of the original portfolios that included all stocks from firms on the lists. This holds in terms of the annual average excess returns as well as in terms of the factor-adjusted returns (alphas). Therefore, this would suggest some relation of stock returns to list inclusion rather than the intrinsic signal of employee satisfaction. However, the alphas from the equal-weighted portfolios are still positive, although not statistically significant, and the Europe-Home portfolio still shows a strong employee satisfaction premium. One should also take into account that the amount of stocks included in these new arrivals and delisted portfolios is very small. For example, average turnover is only 11 for the US lists. Therefore, it is not uncommon to observe smaller returns on these less diversified portfolios, and since the Europe-Home portfolio still exhibits a premium and the alphas on the other delisted portfolios are still positive, it would appear that the premium is related to more than just list publication.

At the same time, one would want to make sure that these results are robust and not driven by outliers. To account for this, I winsorize the returns at the 10% and 90% levels. Tables A12 and A13 in Appendix A3 show the performance measures and coefficient estimates of the factor regressions of the excess equal-weighted and value-weighted portfolio returns, respectively. The average excess returns are generally lower than for the non-winsorized portfolios and, as expected, winsorization generally results in diminished alphas, yet in the case of the four-factor regression the alphas still differ significantly from zero. One should notice that the Europe-Foreign portfolio produces significantly negative alphas when winsorization is applied, even in the case of the one-factor regression. These portfolios are not only not gaining abnormal returns, but even gaining lower returns than a usual portfolio of this factor exposure. In the end, I conclude that apart from the diminished alphas, factor regressions of portfolios with winsorized returns lead to similar conclusions as factor regressions of portfolios with the raw returns. One should also take into consideration that winsorization at the 10% and 90% levels is equivalent to throwing away 20% of the data, which seems to be a rather extreme measure. Therefore, as the conclusions do not differ so much between winsorized and raw returns, I would like to stick to the original results.

For further robustness, I also tried winsorization at the 1% and 99% levels and at the 5% and 95% levels. In the former, the results were nearly identical to the main results without winsorization whereas in the latter the alphas remained a bit higher than in the portfolios with returns winsorized at the 10% and 90% levels, but the main conclusions remained the same. I do not report the results from the winsorized portfolios that were winsorized at the 1% and 99% levels and at the 5% and 95% levels. Next to the standard ordinary least squares regression, I also applied weighted least squares (WLS) regression with weights equal to the inverse of the absolute residual. However, the results were quite similar to the main results. I also do not report these results.

In all, an employee satisfaction premium (in excess of the size, value, and momentum factors) persists beyond the range of Edmans' (2011) sample period, as well as in other geographic regions. Therefore, the author's finding of stocks of the

'100 Best Companies to Work for' earning abnormal excess returns is not specific to the sample that he considers and thus warrants further investigation. Furthermore, from the examination of the average per-month cumulative excess returns and the alternative delisted and new arrivals portfolios, this employee satisfaction premium did not appear to be a mere list publication effect. In this first investigation, there exists some evidence that the quality factor might be contributing to this premium. This is not unexpected because at a first glance a lot of the firms on the lists are strong and stable firms for which it would not be unsurprising if they also scored high on quality. Therefore, the findings so far warrant further investigation into the relation between employee satisfaction and the quality factor. A drawback of this definition of firms with high employee satisfaction, as inclusion in the '100 Best Companies to Work for' lists, is that it does not allow for a sample that includes stocks over a range of different employee satisfaction levels. Furthermore, most list portfolios formed here contain a small amount of stocks, hence inferences made about these portfolios might be inferences about the particular stocks in the samples rather than inferences about high employee satisfaction stocks. In addition, these small portfolios sometimes produce statistically insignificant alphas that are still economically interesting. Larger portfolios would allow for clearer inferences about factor-adjusted abnormal returns in high employee satisfaction stocks. Taking all of this into account, I continue by considering an alternative employee satisfaction proxy that measures employee satisfaction on a more continuous-like scale.

5. FROM LOW TO HIGH EMPLOYEE SATISFACTION

1. DATA AND PORTFOLIO FORMATION

In the above results, I show a first indication of a premium existing on stocks from firms with high employee satisfaction. As previously indicated, I will extend the above research with the addition of another measure of employee satisfaction. This allows me to investigate the relationship between employee satisfaction and stock returns over a range of employee satisfaction levels and it also leads to a larger amount of stocks in employee satisfaction portfolios, which allows for more robust inferences. In this second measure, I proxy employee satisfaction in a firm as its score on the employment conditions section of the RobecoSAM Corporate Sustainability Assessment (CSA). RobecoSAM allots sustainability scores to firms on the basis of a questionnaire and extensive company documentation, as well as media coverage, stakeholder commentaries, and other publicly available sources. Each year RobecoSAM invites the world's largest 2,500 publicly traded firms to participate in the CSA. In the end, RobecoSAM assigns a sustainability score to a wide range of over 2000 companies once a year, thereby covering constituents of major indices. RobecoSAM focuses its criteria on issues that can impact companies' long-term value creation potential.

Total CSA scores are on a scale of 0-100 and the survey questions are divided into different criteria, such as Human Capital Development and Operational Eco-Efficiency. Each criterion falls within each of the three dimensions of corporate sustainability: the economic, environmental, and social dimensions. Each question and Media and Stakeholder analysis is given a weight within its criterion and criteria are then weighted towards the total score. The content of the questions, criteria, and weights vary by industry as this reflects RobecoSAM's belief that sustainability issues leading to company value creation differ between industries. In this thesis, I will not focus on the entire CSA score, but I concentrate on the employee conditions part of the questionnaire. Namely, I make use of an aggregation/combination of the criteria on Labor Practice Indicators and Human Rights (LPI), Human Capital Development (HCD), and Talent Attraction and Retention (TAR), for which scores are available for the period of 2003 until 2015. The LPI criterion evaluates the extent to which a company provides a safe and healthy working environment, as well company policy towards fair treatment practices (such as diversity, equal remuneration, and supporting freedom of association), and human rights. The Human Capital Development criterion focuses on the extent to which companies understand the consequences of their investments in human capital development in terms of outcomes on their business. Lastly, the Talent Attraction and Retention criterion evaluates the companies' ability to attract and retain talented staff which helps companies develop and maintain a competitive advantage. This criterion looks into compensation frameworks (with a focus on long-term incentives).

As mentioned, RobecoSAM assigns scores to a wide range of companies and my sample consists of the universe of stocks for which company scores are simultaneously available on the LPI, HCD, and TAR scores. At large, this sample consists of 4748 stocks for which there are observations on all three of these CSA criteria at some point during the sample period from 2003 to 2015. As this paper will also look into the relation between employee satisfaction and the quality factor, fair comparison demands that the samples used in the separate employee satisfaction investigation of this paper and the investigation linking quality to employee satisfaction correspond to one another. Therefore, my sample will only consist of stocks for which a quality score can also be calculated. For this reason, as is common industry and academic practice, I exclude the stocks from the financial sector from my sample as the measures gross profits to assets and free cash flows to assets (constituents of quality) are not very meaningful for financial firms. Additionally, zero values on the CSA criteria can originate both from the firm receiving a zero score on the criteria or from the incompleteness of the survey questions. Therefore, it appears prudent to exempt zero values from the sample.

These exemptions reduce the sample to 2828 stocks. These stocks constitute a varied coverage over industries and regions. Table 5 provides an overview of the constituents of the sample: the total number of stocks that occur in the sample over the sample period, as well as the mean and median of the number of stocks with available scores on all three criteria over time. Panel A splits the stocks into regions, whereas Panel B shows the sector-split counterpart. A significant part of the sample consists of North American stocks and at each point in time there are also a lot European and Japanese-Pacific stocks in the sample. The Emerging Markets-Asia proportion of the stocks at each point in time is not so large, as CSA scores are mainly available for these stocks near the end of the sample period. The Latin American and other Emerging stocks are not so prevalent in the sample and thus will not be regarded separately in this research. Panel B shows that stocks from the Industrials, Consumer Discretionary, Materials, and IT sectors are the most common in this sample.

TABLE 5

Overview of the Corporate Sustainability Assessment (CSA) Sample

This table shows an overview of the stocks in the Corporate Sustainability Assessment (CSA) sample. These are the stocks for which there are observations on all three of the employee satisfaction criteria for the sample period of 2003 - 2015. Stocks from firms in the financial sector have been excluded, as have stocks with zero values on any of the three employee satisfaction criteria, as zero values can originate from both the firm receiving a zero score on the criteria or from incompleteness of survey questions. Panel A shows a split of the sample by region. Per region, it shows the total number of stocks in the sample over time, that is stocks for which scores on all three of the employee satisfaction criteria are available for at least one time period during the sample period. Furthermore, it shows the average number of stocks and median number of stocks in the sample over time. Panel B contains the same overview for a sample split by sector.

Panel A: Regions

	Full Sample	North America	Europe	Japan-Pacific	Emerging Markets-Eastern Europe, Middle East & Africa	Latin America	Emerging Markets-Asia
Total Number of Stocks in Sample	2828	740	625	562	154	123	616
Average Number of Stocks over Time	1100	309	320	245	37	36	151
Median Number of Stocks over Time	1205	355	348	294	17	18	145

Panel B: Sectors

	Full Sample	Energy	Materials	Industrials	Consumer Discretionary	Consumer Staples	Healthcare	IT	Telecom Services	Utilities
Total Number of Stocks in Sample	2828	198	383	638	510	300	206	300	101	192
Average Number of Stocks over Time	1100	82	152	248	186	113	81	111	45	82
Median Number of Stocks over Time	1205	82	171	290	192	116	96	117	44	79

Apart from the employee satisfaction scores for the stocks in the sample, I also require data on returns and market capitalization on these stocks in order to form portfolios based on employee satisfaction. I also acquire book-to-price ratios for these stocks in order to be able to get indication of the types of stocks in the sample. Observations on these three variables are obtained by matching the stocks in the CSA sample to the Robeco database. This data is originally obtained from FactSet. Again I consider a total returns measure that includes dividends and is denoted in percentage terms. Again, I consider all variables in dollar terms. For further analysis, I also require quality scores. Following the methodology of Kyosev (2013), the latter is constructed out of the following raw variables: accruals, free cash flows to assets, and gross profits to assets. To ensure the exclusion of outliers, I first winsorize these variables at the 1% and 99% level and then, for each of these raw variables, I calculate their z-score on a cross-sectional basis and I take the quality score to be the simple average of these z-scores. Since low accruals are desirable, I take the negative z-score of accruals. I lag these accounting variables 3 months to ensure that they are available at time of portfolio formation. These additional variables are also obtained by linking my universe to the Robeco database.

Tables A4-A7 in the appendix show the yearly descriptive statistics for the returns, market-capitalization, book-to-price ratios, and quality scores of the stocks in the CSA sample. These yearly descriptive are only shown for the full sample, the European sample, and the North American sample because these are the samples that I consider separately in this paper. For comparison reasons I decide to focus on similar regions as those of my analysis of the '100 Best Companies to Work for'. However, as you can see from Table 5, the Latin American sample only contains 36 stocks on average. Further on in this paper I will divide stocks into decile portfolios, this would mean average portfolios of at most 4 stocks for the Latin American sample. Such portfolios are not sufficiently large to draw inferences from; therefore I do not investigate the Latin American sample separately for my analysis with the CSA scores.

One may notice that the stocks in the full CSA sample generally have higher returns than those stocks on the '100 Best Companies to Work for' lists. As the '100 Best Companies to Work for' sample is supposed to only contain stocks with high employee satisfaction and the CSA sample contains stocks over a range of employee satisfaction levels, this suggests that Edmans' (2011) finding of a list premium may be quite particular to his sample period or region under consideration. As mentioned previously, I extend Edmans' (2011) sample through time and over regions. However, when comparing only the European samples, one may notice that during a lot of years stocks on the list had higher mean and median returns relative to the CSA sample. Furthermore, stocks on the '100 Best Companies to Work for' lists have, on average, larger market capitalizations than those of the CSA sample. Therefore, stocks with high employee satisfaction are mainly larger companies. Any premium resulting from these high employee satisfaction stocks will thus not be attributable to the size factor. However, as these appear to be large firms that are likely well-known, it might still be that such a premium stems from reputational advantages or some other commonality between these stocks. Additionally, it can be noticed from Tables A3 and A6 that the book-to-price ratios of the list stocks (so high employee satisfaction stocks) are relatively low, as compared to the book-to-price ratios of the stocks in the CSA sample (which includes stocks over a range of employee satisfaction levels). This links high employee satisfaction stocks to growth stocks and thus a return premium on high employee satisfaction is unlikely to be attributable to the value factor.

Having defined the sample and investigated the characteristics of the stocks in the sample, I now also inspect the scores on the LPI, HCD, and TAR criteria of the CSA survey more closely. Firstly, one should be aware of some of the biases in these employee satisfaction criteria scores. For example, RobecoSAM often corrects for a size bias in the sample as it finds that companies with higher market capitalizations are often assigned higher scores. This would in practice lead to a negative exposure to the size (SMB) factor when forming a portfolio of high CSA scores. Furthermore, one should also be aware that there might be some differences in scores between stocks from different regions. A region bias is relevant in the case that a global analysis is performed on the CSA scores. I remove the size bias and region bias simultaneously by performing a cross-sectional regression: at each point in time I regress each of the three criteria scores on a constant, the natural logarithm of the market capitalization, and 5 region dummies, taking the Latin American case to be the base case. I then subtract the size coefficient multiplied by the natural logarithm of the market capitalization and the region coefficients multiplied by their corresponding dummies from the original score, and retain these values as the new score. Lastly, one should also be aware that there might be some differences in scores between sectors. This will not be corrected for in the general data because such a sector bias may again be region-specific and correcting for it on a global level, or even on a regional level might create new bias within the data when considering an alternatively specified sample. However, later on in this paper I show results for portfolios which are made sector-neutral over the samples that I consider whether it be a global or a regional sample. This corrects for any bias regarding sectors that might appear in the results.

Table 6 shows some descriptive statistics of these (transformed) employee satisfaction scores. Panel A shows these statistics for the full sample for which these scores are available, whereas Panel B shows the descriptive statistics of those stocks that appear both on the '100 Best Places to Work for' lists and have available CSA employee satisfaction scores. The overlap between these two samples consists of 184 stocks. These statistics are calculated for the yearly scores and then averaged across time. One may observe that the mean and median of the scores of firms on the '100 Best Places to Work for' lists are generally higher than for the entire sample. Indeed, a straightforward paired sample *t*-test on the series of yearly average scores across firms indicates that the TAR and LPI scores are significantly higher (even statistically significant at the 1% significance level) for the firms on the list. This confirms consistency between the two employee satisfaction measures that I use in this paper.

One should also note that although these employee satisfaction scores will provide some common signals, their correlation is not incredibly high. The TAR and HC scores have a correlation of about 0.45, the LPI and HC scores have a

TABLE 6

Summary Statistics of the Employee Satisfaction Criteria

This table shows the descriptive statistics of the individual employee satisfaction criteria: Human Capital Development (HCD), Talent Attraction and Retention (TAR), Labor Practice Indicators and Human Rights (LPI). The size and region bias have already been removed from the scores by cross-sectional regressions. The descriptive statistics shown in this table concern the residual scores. The descriptive statistics of the scores are calculated for the yearly scores and then averaged across time. Panel A shows these statistics for all stocks in the Corporate Sustainability Assessment (CSA) sample, while panel B shows these statistics for the 184 stocks which appear on the '100 Best Companies to Work for' lists and for which employee satisfaction scores are also available. The last column in Panel B shows the *p*-value of a paired sample *t-test* that compares the yearly across firm-average scores of the '100 Best Companies to Work for' sample to those of the entire CSA sample. Panel C shows descriptive statistics of monthly return series (in percentage terms) of regional value-weighted long-short portfolios constructed by going long in the stocks in the top decile of employee satisfaction level (when considering the aggregate employee satisfaction score) and short in the stocks in the bottom decile of employee satisfaction level.

Panel A: Corporate Sustainability Assessment Sample

	Mean	Std. Dev.	Min	Max	Median	Excess Kurtosis	Skewness	# Obs
HCD	-15.27	24.65	-66.26	55.34	-18.75	-0.54	0.42	1101
TAR	-3.05	15.32	-41.84	46.12	-7.22	-0.28	0.67	1480
LPI	17.80	13.85	-28.21	61.15	16.17	-2.86	0.39	1482

Panel B: '100 Best Companies to work for' Sample

	Mean	Std. Dev.	Min	Max	Median	Excess Kurtosis	Skewness	# Obs	Paired t-test (*p*-value)
HCD	-11.45	25.65	-56.55	45.93	-10.94	-0.80	0.23	114	0.17
TAR	5.66	17.08	-23.96	44.11	5.16	-0.93	0.24	132	0.00
LPI	30.59	13.72	0.66	66.09	30.09	-3.15	0.26	132	0.00

Panel C: Top-minus-Bottom Portfolios

	Mean	Std. Dev.	Min	Max	Median	Excess Kurtosis	Skewness	# Obs
North America	0.04	2.86	-7.06	11.73	-0.28	2.70	1.02	147
Europe	0.30	2.71	-6.85	8.40	0.20	0.15	-0.02	147
Japan-Pacific	0.14	3.70	-12.66	11.19	-0.22	1.20	0.13	147
Emerging Markets-Asia	-0.73	6.12	-30.60	17.75	0.00	5.51	-1.26	147

correlation of about 0.37, and the LPI and TAR scores have a correlation about 0.42. This indicates that these measures do contain different signals and hence it makes sense to combine them into one final employee satisfaction (ES) score. For this, I consider the method that Asness et al. (2015) use to combine their different quality constituent measures into one quality score. Namely, I construct the ES score as the z-score of the sum of the z-scores of the individual scores:

$$ES = z(z(HC) \ + z(TAR) + z(LPI)) \tag{5}$$

Finally, this provides a quantitative measure for employee satisfaction over a range of employee satisfaction levels. As these ES scores are on a continuous scale (rather than logical values like 'Best Companies to Work for' list inclusion), it is possible to use the often-used rank-portfolio approach as in, among others, Fama and French (1992). Therefore, I form decile portfolios, assigning the stocks of the firms with the highest employee satisfaction into the top decile and the stocks of the firms with the lowest employee satisfaction into the bottom decile. As the CSA survey scores are published in September on a yearly basis, portfolios are formed at the end of September and held for the duration of the next year. I do however want to investigate monthly returns, therefore I obtain equal-and value-weighted monthly portfolio returns for the months in between. Since equal-weighted portfolios lead to similar overall conclusions as the value-weighted portfolios, I only report the results of the value-weighted portfolios here to keep the overview of the results compact. Again, although portfolio constituent stocks are selected on a yearly basis, their weights within the value-weighted portfolios are updated on a monthly basis using the monthly observations on market capitalization. If employee satisfaction is related to returns, one expects the excess returns to increase along the decile portfolios when moving from the bottom to the top portfolio.

Panel C of table 6 shows the descriptive statistics of monthly returns on value-weighted long-short portfolios that are constructed by buying the stocks in the top employee satisfaction decile and shorting the stocks in the bottom employee satisfaction decile. Peculiarly, one may notice that the average returns of such long-short portfolios differ a lot between the regions. At a first glance, a premium on employee satisfaction appears to be present within the European stocks, whereas the North American portfolio attains average returns of nearly zero and a negative median. The Japan-Pacific portfolio has positive average returns, yet its median is quite negative and the Emerging Markets – Asia portfolio even has negative average returns. This is also in line with the earlier finding in this paper that a premium on the 'Best Companies to Work for' is more prevalent in Europe. This can be due to the strong labour conditions laws in Europe and thus the highest employee satisfaction firms being those firms with the best labour conditions within a set of firms of very good labour conditions. However, this may also be due to the fact that the data on ES scores in Europe is more accurate than that of other regions, a bias that RobecoSAM has confirmed. For this reason and because Edmans (2011) already extensively investigates the employee satisfaction premium in the US, I will firstly restrict my main analysis to European stocks and elaborate to the global sample afterwards.

2. METHODOLOGY: TESTING FOR ABNORMAL RETURNS

As in the previous analysis with the '100 Best Companies to Work for', the first thing that I want to examine with these portfolios is whether high ES scores lead to higher excess returns. This is again done by regressing the decile portfolios on the CAPM (equation 2), Carhart's (1997) four-factor model (equation 3), and a third model which is Carhart's (1997) four-factor model augmented by the quality factor rather than the QMJ factor. This last model is obtained by replacing the QMJ factor in equation 4 by the quality (Q) factor.

The sorted portfolios' alphas from the three factor regressions will provide a first indication of whether unexplained return alpha increases with employee satisfaction and can evaluate whether each portfolio outperforms significantly on portfolio-specific basis, however to conclude a positive relationship between returns and employee satisfaction an overall test is necessary. I consider two such tests. The first such test is the GRS test, developed by Gibbons, Ross, and Shanken (1989), which tests whether the intercepts from multiple regression models, the alphas in equations 2, 3, and 4 are jointly equal to zero. I calculate the test statistic as follows:

$$GRS = \left(\frac{T-n-k}{n}\right)\left[\frac{\hat{\alpha}'\hat{\Sigma}^{-1}\hat{\alpha}}{1+\bar{f}'\bar{\Omega}^{-1}\bar{f}}\right] \qquad \sim \qquad F(n, T-n-k) \tag{6}$$

where T is the number of available time series observations and n is the number of portfolios under consideration, k is the number of estimated coefficients, $\hat{\alpha}$ is the estimated alpha in regressions 2, 3, or 4, while $\bar{f}'$ is the time series mean of the factors included in the regression (the market factor for equation 2, the market, size, value, and momentum factors for equation 3, and the set of factors from equation 3 augmented by the quality factor in equation 4). Lastly, $\hat{\Sigma}$ and $\bar{\Omega}$ are the estimated covariance matrix of the regression residuals across the decile portfolios and the sample variance matrix of the factors, respectively. With this test, I test whether the alphas are jointly equal to zero, however this test does not indicate whether alpha increases monotonically across the decile portfolios. Hence, from the GRS test one may not conclude a monotonically increasing relationship between employee satisfaction and portfolio returns. Patton and Timmermann (2010) propose a more appropriate test for this consideration in which they test an alternative hypothesis of the minimum differential among the sorted average returns being greater than zero, yet Wolf and Romano (2013) show that such a test does not take into account the cases in which the relationship is weakly increasing/decreasing. The authors extend the test of Patton and Timmermann (2010) by stipulating the following test hypotheses:

$$H_0:\ min_i \Delta_i \leq 0 \qquad vs. \qquad H_1:\ min_i \Delta_i > 0 \tag{7}$$

where Δ_i is the population mean of the difference in returns between neighboring decile portfolios (formed according to employee satisfaction level) with $i = 1, \ldots, 9$ since there are ten portfolios. That is to say, Δ_1 is the population mean of the difference between the excess returns of the bottom decile portfolio and the excess returns of the second decile portfolio,

Δ_2 corresponds to the population mean of the return differentials between the second and third decile portfolio, and so on.

To test the null hypothesis in equation 7, Wolf and Romano (2013) calculate a t-statistic on the estimator of $min_i \Delta_i$. The estimator on the differential i is calculated as the sample mean of the return differentials i over the sample period (T):

$$\hat{\Delta}_{T,i} = \bar{d}_{T,i} = \frac{1}{T}\sum_{i=1}^{T} d_{t,i} \qquad , \qquad i = 1, \ldots, 9 \tag{8}$$

where $\hat{\Delta}_{T,i}$ is the mean return differential estimator of differential i and $d_{t,i}$ is the difference in excess returns between neighboring decile portfolios at time t. Following this, a t-statistic is calculated for each of the nine differential estimators:

$$t_{T,i} = \frac{\hat{\Delta}_{T,i}}{\hat{\sigma}_{T,i}} \qquad , \qquad i = 1, \ldots, 9 \tag{9}$$

where $\hat{\sigma}_{T,i}$ is the sample standard deviation of the return differentials of differential i. In the presence of serial correlation, HAC standard errors are used rather than the regular sample standard deviation. Finally, the test statistic is obtained by taking the minimum t-statistic among the nine differential t-statistics:

$$t_T^{min} = min_i t_{T,i} \qquad , \qquad i = 1, \ldots, 9 \tag{10}$$

As this statistic will not have a standard distribution, the authors compare different ways of computing a critical value for this test. In this thesis, I will make use of their Cons test as this test performs very well and is easy to use in practical application. This test takes the worst-case scenario parameter as null parameter i.e. the null parameter that results in the largest critical value possible as this will be the most difficult null parameter to reject in favor of the alternative hypothesis of strictly positive mean return differentials. In the case of the null hypothesis postulated in equation 7, the worst-case scenario parameter would be

$$\boldsymbol{\Delta_0} = (\infty, \infty, \ldots, 0, \infty, \infty) \tag{11}$$

with $\boldsymbol{\Delta_0}$ a vector of null parameters for Δ_i for all $i = 1, \ldots, 9$. If the position of the zero differential is known, then the implied sampling distribution of the test statistic can be approximated by a univariate bootstrap. Since the data being considered constitutes a time series, I make use of moving block bootstrapping to preserve the autocorrelation structure of the returns and factors. I take a block window of 12 months, allowing overlap between blocks. I follow Wolf and Romano (2013) in the calculation of the critical value distribution, which is described in Algorithm A1 in Appendix A5. Since, of course, the position of the zero mean differential in the null parameter is unknown, the univariate bootstrap must be repeated for all differentials, varying the location of the zero entry in $\boldsymbol{\Delta_0} = (\infty, \infty, \ldots, 0, \infty, \infty)$. The largest critical value among the nine resulting critical values needs to be used to compare the t-statistic of the minimum mean return differential to.

I apply this test to both the raw excess returns of the portfolios, implementing the test exactly as described above in the manner that Wolf and Romano (2013) intend. I also apply this test to the alphas of the factor regressions in equations 2-4 rather than the population mean of the differentials. In this case, $\hat{\Delta}_{T,i}$ is the $\hat{\alpha}_i$that results when regressing the differential i series on the factors and $\hat{\sigma}_{T,i}$ is the standard error on this $\hat{\alpha}_i$. I thus replace the original estimator of the sample mean and use alpha as an estimator instead. Newey-West standard errors are used in the case that serial correlation is present in the regression residuals.

As employee satisfaction will likely be a smaller effect than other documented factors, a monotonically increasing sequence of alphas/ mean returns will probably not be observed but one may rather observe a general increase in the alpha/mean return pattern. This is indeed what I find later on in this paper. Therefore, this test by Wolf and Romano (2013) is very strict for the purpose considered and, if applied as they intend, it will always reject the null hypothesis of monotonically increasing expected excess returns/alphas. Since I want to investigate whether the alphas are generally increasing, I apply the tests only on a subset of the decile portfolios. The bottom ES portfolio performing worse than the top ES portfolios is centrifugal to my investigation and, as you will read later on, this employee satisfaction effect is more prevalent within high ES stocks. Therefore, I apply this Wolf-Romano test on the following subset of portfolios: the bottom portfolio and the top three decile portfolios.

3. Main Results

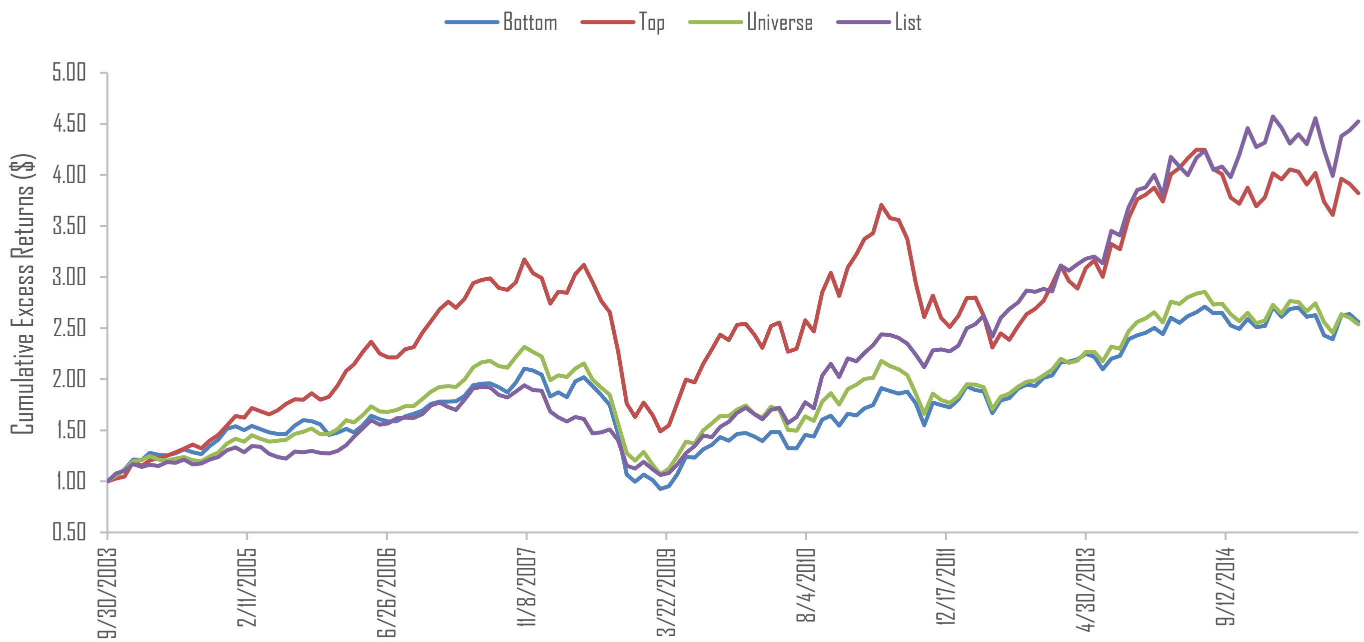
The first investigation of top-minus-bottom portfolios of portfolios constructed from ES decile sorts showed that the European top-minus-bottom exhibited positive average excess returns of large magnitude. In this section, I first present the results from employee satisfaction sorts for the European sample. I decide to firstly focus on the European Sample as the over-time average amount of stocks in the CSA sample is the largest for this region and RobecoSAM has claimed that its European CSA scores are the most accurate in the sample. Furthermore, I documented a strong European ES effect in my analysis of the '100 Best Companies to Work for' and Edmans (2011) already extensively investigates the ES effect in the US sample, but does not focus on Europe. Later on in this section, I also present results for the global sample and results for the North American sample can be found in appendix A4.

Figure 1 shows the cumulative compound excess returns of the value-weighted top and bottom decile ES portfolios of European stocks when 1 dollar is invested in the portfolios at the end of September 2003. The graph also depicts the corresponding cumulative excess returns of 1 dollar being invested in a value-weighted portfolio of all European stocks in the sample (universe portfolio).

FIGURE 1

Performance of European Employee Satisfaction (ES) Portfolios

This figure shows the value-weighted cumulative compound excess returns of 1 dollar being invested in the European ES portfolios at the end of September 2003. Portfolios are re-balanced on a yearly basis and held until December 2015. Bottom is the portfolio containing the stocks in the lowest ES decile, while Top is the portfolio containing the stocks in the highest ES decile. Universe is the value-weighted portfolio of all stocks in the European CSA universe. List corresponds to the Europe-Home portfolio, which is the portfolio of the stocks of the '100 Best Companies to Work for' in Europe list that are also traded on a European exchange. The cumulative compound returns are calculated as $(1 + r_1)(1 + r_2) \ldots (1 + r_T)$.



One may observe that the top portfolio largely outperforms the universe portfolio, yet the bottom portfolio performs quite similarly to the universe portfolio. Hence, the earlier observed outperformance of the top-min-bottom portfolio is mainly attributable to the outperformance of the top portfolio and shorting the bottom portfolio has little added value. The latter observation might be because the European sample only contains firms with good employee satisfaction due to labour conditions laws and hence firms with very low levels of employee satisfaction are not found within the sample. The bottom decile would thus contain firms with medium levels of employee satisfaction. At the same time, the fact that low ES stocks do not substantially underperform may be due to a data bias. It is possible, since CSA scores are available for the constituents of major indices, that the sample contains mainly stocks with medium and high ES relative to their peers within the region and that the sample does not contain many low ES stocks. Additionally plotted in Figure 1 are the cumulative compound excess returns of the Europe-Home portfolio. As discussed earlier, this portfolio consists of the European-traded stocks of the companies on the European 'Best Companies to Work for' list. Observe that this portfolio performs similarly to the universe portfolio until 2010, after which its performance rises steeply to join that of the top ES portfolio. The superior performance of the 'Best Companies to Work for' stocks thus originates mainly from outperformance in the later years of the sample. As the companies on the list generally scored better on the employee satisfaction criteria, it is not entirely unsurprising that its performance is, at some point, similar to that of a high ES portfolio when measuring ES by the scores on the employee satisfaction criteria of the CSA.

Furthermore, Table 7 shows a quantitative overview of the decile portfolios, sorted on ES, as well as the top-minus-bottom portfolio. Panel A displays the performance measures. These measures have been calculated from monthly excess returns and then annualized. The portfolios appear to perform quite similarly in terms of average excess returns and Sharpe ratios and one cannot observe a clear increasing pattern when moving along the decile portfolios. However, one may notice that the two top-most portfolios clearly outperform the others in terms of average excess returns and that the bottom portfolio does not underperform. Therefore, the top-minus-bottom portfolio performs significantly worse than the universe portfolio and one would better invest in a long-only portfolio in this case. In fact, Wolf and Romano's (2013) Cons test strongly rejects the null of a monotonic increasing pattern in excess returns in the subset of the bottom portfolio and the top three portfolios. This is likely due to the bottom portfolio outperforming the 8th decile portfolio.

Panels B, C, and D show the results of factor regressions of the monthly excess returns of the decile portfolios on the market factor, the factors from Carhart's four-factor model, and the factors from Carhart's four-factor model plus the quality factor. These panels also show the results of the GRS and Wolf-Romano (WR) tests on the resulting alphas from the three regressions. For each of the regressions, I test for heteroscedasticity and serial correlation in the error term, ε_{it}, using the Breusch-Pagan and Ljung-Box Q tests, respectively. In the case that either is found to be present at the 5% significance level, I make use of Newey-West standard errors. Alphas that differ (statistically) significantly from zero are only observed in the case of the ninth and top decile portfolios. These portfolios thus exhibit a positive premium in excess of the premium on these known factors. The alphas on the other portfolios are generally smaller (sometimes even negative) than those of the top two portfolios, however these alphas do not differ statistically significantly from zero, even at the 10% significance level, and these alphas are not monotonically increasing in the ES score, which increases across the portfolios. For each of the factor models, I also apply a GRS test which does not reject the null hypothesis of the alphas being jointly zero (not even at the 10% significance level), confirming the lack of pattern in the alphas of the decile portfolios, sorted according to the ES score. The same goes for the Wolf-Romano test which has a p-value of 1.00, not rejecting the null hypothesis of no monotonically increase in the subset of the bottom alpha and three top portfolio alphas for all three factor regressions.

In addition, the coefficient on the market factor is, as expected, around 1. Also unsurprising is the significant negative exposure to the size factor for some of the portfolios as these portfolios are value-weighted. Also, most of the portfolios appear to be growth stocks according to their negative coefficients on the value factor, except for the top portfolio and, by consequence, the top-minus-bottom portfolio. Firms that score high on employee satisfaction are thus generally firms

TABLE 7

Factor-Adjusted Returns of European Employee Satisfaction (ES) Decile Portfolios

This table presents performance measures and regression results of European value-weighted decile portfolios, sorted on ES. Bottom contains the stocks with lowest ES levels, Top contains highest ES level stocks. Universe is the value-weighted portfolio of all stocks in the European CSA universe. Portfolio returns are available for October 2003 - December 2015. Panel A shows annual performance measures. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM, 4-factor, and 5-factor regressions, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality (Q) factor. α is the regression intercept. The returns on the European Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the Q factor have been calculated from the European CSA universe. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding p-value, and the p-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	10.01	8.41	10.14	7.54	6.92	9.14	9.93	7.28	12.99	13.96	3.62	9.59		0.96
Volatility	19.05	18.02	17.44	16.77	18.19	17.44	18.92	18.60	20.14	20.61	9.39	17.57		
Sharpe	0.53	0.47	0.58	0.45	0.38	0.52	0.52	0.39	0.64	0.68	0.39	0.55		

Panel B: CAPM

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.16	0.09	0.24	0.06	-0.04	0.15	0.15	-0.03	0.33***	0.40**	0.23	1.28	0.25	1.00
	(0.93)	(0.49)	(1.63)	(0.36)	(-0.22)	(1.05)	(1.04)	(-0.26)	(3.46)	(2.47)	(0.84)			
β_{Mkt}	0.93***	0.86***	0.83***	0.80***	0.87***	0.85***	0.94***	0.91***	1.01***	1.02***	0.09			
Adj. R^2	0.87	0.82	0.82	0.83	0.84	0.87	0.90	0.87	0.91	0.89	0.03			

Panel C: 4-Factor Regressions

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.10	0.01	0.17	-0.11	-0.12	0.13	0.06	-0.01	0.30**	0.37**	0.26	0.98	0.47	1.00
	(0.78)	(0.07)	(1.20)	(-0.72)	(-0.71)	(1.00)	(0.41)	(-0.05)	(2.46)	(2.18)	(1.28)			
β_{Mkt}	1.05***	0.92***	0.90***	0.91***	0.95***	0.90***	1.00***	0.93***	1.05***	1.00***	-0.05***			
β_{SMB}	0.05	-0.11***	-0.34*	-0.14***	-0.26***	-0.37***	-0.19	-0.12	-0.02	0.05	0.01			
β_{HML}	-0.60***	-0.22	-0.22***	-0.37***	-0.25**	-0.15	-0.17**	-0.14*	-0.18*	0.17*	0.77***			
β_{MOM}	-0.05	0.05	0.08*	0.12***	0.08	0.05	0.08**	-0.03	0.01	0.05	0.10*			
Adj. R^2	0.90	0.83	0.85	0.86	0.86	0.89	0.91	0.87	0.92	0.90	0.24			

Panel D: 5-Factor Regressions (Includes Quality Factor)

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.09	0.05	0.14	-0.19	-0.19	0.09	0.04	-0.02	0.31***	0.40**	0.30	1.13	0.34	1.00
	(0.60)	(0.33)	(0.82)	(-1.19)	(-1.10)	(0.66)	(0.27)	(-0.11)	(2.76)	(2.32)	(1.44)			
β_{Mkt}	1.05***	0.90***	0.91***	0.95***	0.98***	0.91***	1.01***	0.93***	1.04***	0.98***	-0.07			
β_{SMB}	0.05	-0.13	-0.32***	-0.09	-0.22**	-0.35***	-0.18**	-0.12	-0.03	0.04	-0.02			
β_{HML}	-0.59***	-0.26**	-0.20**	-0.31***	-0.19*	-0.12	-0.15*	-0.13*	-0.19	0.14	0.74***			
β_{MOM}	-0.06	0.06	0.07	0.11**	0.06	0.04	0.08*	-0.03	0.01	0.05	0.11*			
β_{Q}	0.03	-0.15	0.10	0.28***	0.25**	0.12	0.07	0.03	-0.06	-0.11	-0.14			
Adj. R^2	0.90	0.83	0.85	0.86	0.86	0.89	0.91	0.87	0.92	0.90	0.24			

with high book-to-market ratios on their stocks, this contrasts with earlier finding of the Europe-Home list portfolio loading negatively on the value factor. It should be noted that these decile portfolios contain a lot more stocks, the decile portfolios of 2015 contain about 50 stocks, whereas the Europe-Home list portfolio contains 8 stocks on average. Therefore, inferences made about the Europe-Home portfolio might be inferences about the particular stocks in the portfolio rather than high employee satisfaction stocks, for which the portfolios based on the CSA scores provide a better proxy. Lastly, the addition of the quality factor only increases the alphas on the ninth and top portfolio, rather than reducing it. Therefore, the outperformance of these portfolios cannot be explained by the quality factor. The top-most portfolios, as well as the top-minus-bottom portfolio, are even negatively exposed to the quality factor while some of the lower ES portfolios even have positive coefficients on the quality factor that differ significantly from zero. The effects of quality and of employee satisfaction on stocks returns thus appear not to be overlapping, nor are they signals for the same effect, as was initially expected.

One should note that in some industries or sectors employee satisfaction might be more important for the company's financial performance, and thus its stock returns, than in other sectors. For example, in the IT industry a company will thrive more when more innovations and patents are achieved, something that might depend highly on the degree of employee satisfaction, while other industries depend less on innovations. Furthermore, some sectors might have generally higher ES scores due to data bias. Additionally, (especially relevant since the sample period is quite short), some sectors might generally tend to achieve higher stock returns over certain periods of time. For these reasons I also perform sector-neutral sorts on the ES scores. I do this by restricting the total portfolio weights in stocks of a specific sector to equal the weight of that sector in the universe portfolio. Again, I focus on the European stocks.

Figure 2 graphically depicts the cumulative compound excess returns of the top and bottom decile portfolios when 1 dollar is invested into these sector-neutral portfolios at the beginning of the sample period. Similarly to the regular sorts, the top portfolio performance is superior to that of the universe portfolio. However, in the sector-neutral case, the bottom portfolio also slightly underperforms the universe portfolio, especially towards the end of the sample period.

FIGURE 2

Performance of European Sector-Neutral Employee Satisfaction (ES) Portfolios

This figure shows the value-weighted cumulative compound excess returns of 1 dollar being invested in the European sector-neutral ES portfolios at the end of September 2003. Portfolios are re-balanced on a yearly basis and held until December 2015. Bottom is the portfolio containing the stocks in the lowest ES decile, while Top is the portfolio containing the stocks in the highest ES decile. Universe is the value-weighted portfolio of all stocks in the European CSA universe. The cumulative compound returns are calculated as $(1+r_1)(1+r_2)\ .\ \ .\ \ .(1+\ r_T)$.

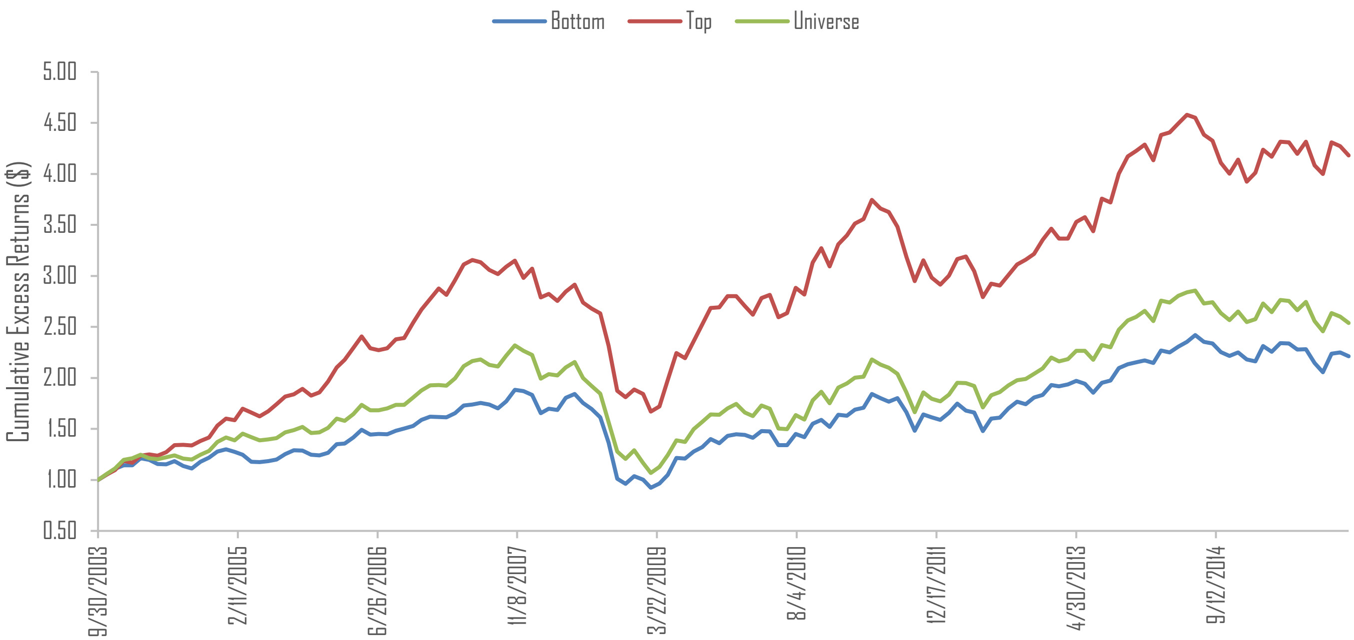


Table 8 shows the quantitative results of these sector-neutral sorts. Notice that the top portfolio from these sector neutral sorts outperforms even more than that of the regular sorts. In fact, it has just a slightly higher average excess return, but much higher Sharpe ratio and higher alphas for all three of the factor regressions. In addition, although a monotonically increasing pattern in the excess returns of the subset of the bottom and top three decile portfolios is still not found according to the Cons test of Wolf and Romano (2013), the test's *p*-value is much lower than for the regular European sorts. Moreover, the top-minus-bottom portfolio alphas are large positive values that differ significantly from zero in a statistical sense. Furthermore, while the bottom portfolio is still not attaining negative average excess returns, it is underperforming the universe (in contrast to the bottom portfolio from the regular sorts which slightly outperforms the universe portfolio in terms of average excess returns) and its factor-adjusted excess returns (alphas) are slightly lower than those of the regular sort bottom portfolio. The GRS tests indicate that the alphas of these portfolios do jointly differ from zero at the 5% significance level for all three factor regressions. Furthermore, the Wolf-Romano test on the subset of the one- and four-factor alphas from the bottom and top three decile portfolios rejects the null hypothesis in favor of the alternative hypothesis of monotonically increasing alphas in this subset of portfolios. Taking both the GRS test and the Wolf-Romano test into account, I thus conclude that sector-neutrality allows for a clearer differentiation of the effect of different levels of ES on excess stock returns. Furthermore, from the addition of the quality factor to these regressions,

TABLE 8

Factor-Adjusted Returns of European Sector-Neutral Employee Satisfaction (ES) Decile Portfolios

This table presents performance measures and regression results of European sector-neutral value-weighted decile portfolios, sorted on ES. Bottom contains the stocks with lowest ES levels, Top contains highest ES level stocks. Universe is the value-weighted portfolio of all stocks in the European CSA universe. Portfolio returns are available for October 2003 - December 2015. Panel A shows annual performance measures. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM, 4-factor, and 5-factor regressions, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality (Q) factor. α is the regression intercept. The returns on the European Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the Q factor have been calculated from the European CSA universe. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding p-value, and the p-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	8.38	8.37	9.46	5.47	9.03	8.57	8.32	9.28	11.34	13.98	5.21	9.59		0.34
Volatility	17.43	16.97	16.02	18.12	17.66	16.59	18.34	18.20	19.18	16.88	8.51	17.57		
Sharpe	0.48	0.49	0.59	0.30	0.51	0.52	0.45	0.51	0.59	0.83	0.61	0.55		

Panel B: CAPM

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.09	0.10	0.22*	-0.18	0.13	0.13	0.04	0.13	0.24**	0.53***	0.44*	2.43	0.01	0.00
	(0.70)	(0.61)	(1.78)	(-1.48)	(0.78)	(0.98)	(0.31)	(0.85)	(2.13)	(3.80)	(1.80)			
β_{Mkt}	0.85***	0.84***	0.78***	0.91***	0.87***	0.82***	0.92***	0.89***	0.96***	0.83***	-0.02			
Adj. R^2	0.86	0.89	0.87	0.92	0.89	0.88	0.91	0.88	0.92	0.88	-0.01			

Panel C: 4-Factor Regressions

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.02	0.07	0.24*	-0.20	0.05	0.14	-0.03	0.07	0.22	0.54***	0.51**	2.28	0.02	0.01
	(0.19)	(0.63)	(1.97)	(-1.55)	(0.36)	(1.20)	(-0.26)	(0.45)	(1.60)	(3.63)	(2.51)			
β_{Mkt}	0.94***	0.90***	0.82***	0.94***	0.92***	0.83***	0.96***	0.94***	1.00***	0.82***	-0.12***			
β_{SMB}	0.15	0.03	-0.07	-0.01	-0.16**	-0.28***	-0.09	-0.01	-0.05	0.16	0.01			
β_{HML}	-0.44***	-0.31***	-0.25***	-0.15**	-0.13	-0.06	-0.10	-0.15*	-0.16**	0.04	0.48***			
β_{MOM}	-0.03	-0.03	-0.05	-0.01	0.07*	0.02	0.07*	0.03	0.00	-0.02	0.01			
Adj. R^2	0.88	0.91	0.87	0.92	0.90	0.90	0.92	0.88	0.92	0.88	0.10			

Panel D: 5-Factor Regressions (Includes Quality Factor)

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.06	0.08	0.23*	-0.23*	0.05	0.11	-0.07	0.06	0.22	0.56***	0.50**	2.51	0.01	0.50
	(0.56)	(0.62)	(1.85)	(-1.81)	(0.37)	(1.12)	(-0.48)	(0.39)	(1.56)	(3.66)	(2.40)			
β_{Mkt}	0.92***	0.90***	0.83***	0.96***	0.92***	0.85***	0.97***	0.94***	1.00***	0.80***	-0.12**			
β_{SMB}	0.12	0.02	-0.06	0.01	-0.16**	-0.27***	-0.07	-0.01	-0.05	0.14	0.02			
β_{HML}	-0.47***	-0.32***	-0.24***	-0.12	-0.13	-0.04	-0.08	-0.14	-0.16*	0.02	0.50***			
β_{MOM}	-0.02	-0.03	-0.05	-0.02	0.07*	0.02	0.06	0.03	0.00	-0.02	0.00			
β_{Q}	-0.15	-0.03	0.03	0.13	-0.01	0.09	0.11	0.03	0.01	-0.09	0.05			
Adj. R^2	0.88	0.90	0.87	0.92	0.90	0.90	0.92	0.88	0.92	0.88	0.09			

I can conclude that when taking sector-bias into account the ES effect is still shown to be a separate effect from the quality premium.

Up to this point I considered ES sorts for the European stocks. I now extend my analysis to the global sample. I present the results for sector-neutral sorts here, while the results for the regular sorts are shown in appendix A4. Figure 3 shows the cumulative excess returns of the top and bottom portfolios for sector-neutral ES sorts. Strikingly, one may observe from Figure 3 that, in addition to substantial outperformance of the top portfolio, the global sector-neutral sort bottom portfolio also exhibits some more underperformance than its European counterpart. This difference between the global and European bottom portfolios is very much in line with the interpretation that the labor condition laws in Europe lead to employee satisfaction generally being higher in Europe than in other parts of the world.

FIGURE 3

Performance of Global Sector-Neutral Employee Satisfaction (ES) Portfolios

This figure shows the value-weighted cumulative compound excess returns of 1 dollar being invested in the global sector-neutral ES portfolios at the end of September 2003. Portfolios are re-balanced on a yearly basis and held until December 2015. Bottom is the portfolio containing the stocks in the lowest ES decile, while Top is the portfolio containing the stocks in the highest ES decile. Universe is the value-weighted portfolio of all stocks in the entire CSA universe. The cumulative compound returns are calculated as $(1 + r_1)(1 + r_2) \, . \; . \; . (1 + \, r_T)$.

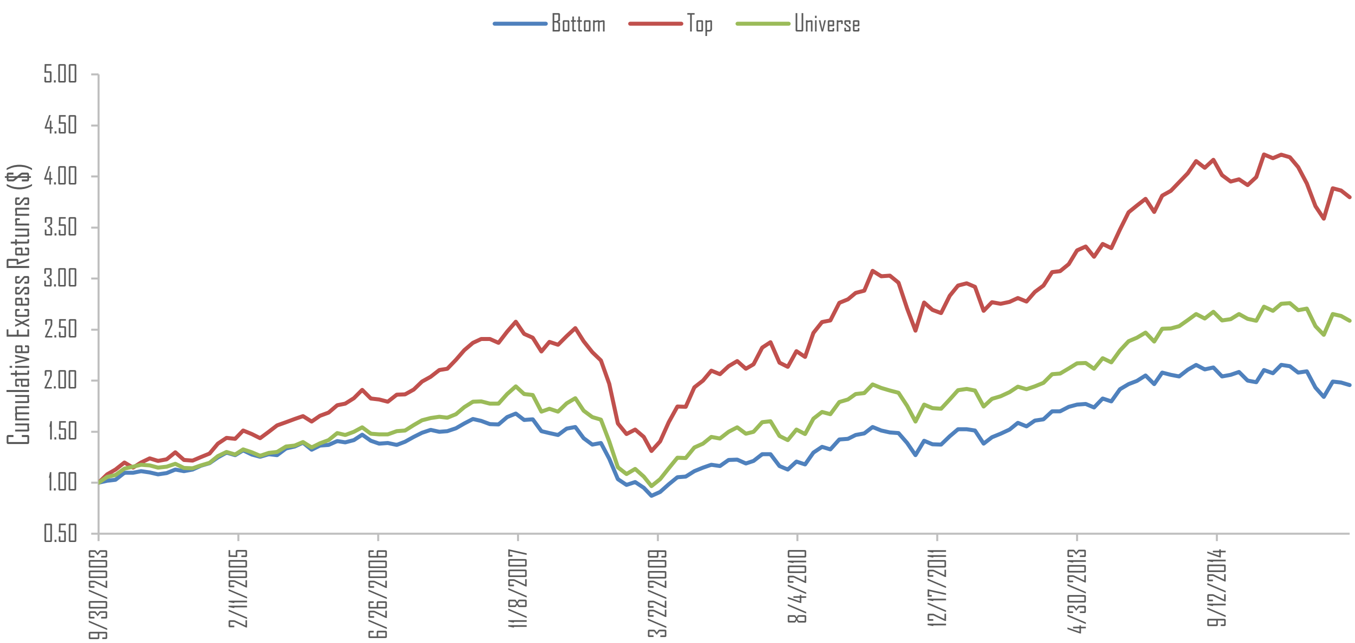


Table 9 shows the quantitative results of these global sector-neutral sorts. Indeed, the average excess returns on the bottom portfolio are lower than in the European case, leading to a slightly higher average returns on the top-minus-bottom portfolio. At the same time, on an annual basis, the average excess returns of the top portfolio are about 1% lower than those of the European top portfolio. Furthermore, this top-minus-bottom portfolio also does not outperform

TABLE 9

Factor-Adjusted Returns of Global Sector-Neutral Employee Satisfaction (ES) Decile Portfolios

This table presents performance measures and regression results of global sector-neutral value-weighted decile portfolios, sorted on ES. Bottom contains the stocks with lowest ES levels, Top contains highest ES level stocks. Universe is the value-weighted portfolio of all stocks in the CSA universe. Portfolio returns are available for October 2003 - December 2015. Panel A shows annual performance measures. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM, 4-factor, and 5-factor regressions, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality (Q) factor. α is the regression intercept. The returns on the global Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the Q factor have been calculated from the entire CSA universe. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding p-value, and the p-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	6.71	8.61	8.06	9.23	7.74	10.00	7.32	8.62	9.11	12.92	5.85	9.29		0.32
Volatility	14.30	15.36	16.38	15.67	16.09	14.78	15.71	16.07	16.18	15.90	6.88	14.99		
Sharpe	0.47	0.56	0.49	0.59	0.48	0.68	0.47	0.54	0.56	0.81	0.85	0.62		

Panel B: CAPM

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	-0.02	0.08	0.00	0.11	-0.01	0.21*	-0.04	0.06	0.08	0.40***	0.42**	1.50	0.14	0.00
	(-0.30)	(0.93)	(0.02)	(1.16)	(-0.09)	(1.75)	(-0.42)	(0.49)	(0.83)	(3.15)	(2.58)			
β_{Mkt}	0.88***	0.96***	1.01***	0.98***	0.99***	0.92***	0.98***	0.99***	1.01***	0.97***	0.09**			
Adj. R^2	0.92	0.93	0.90	0.94	0.91	0.92	0.94	0.91	0.94	0.89	0.03			

Panel C: 4-Factor Regressions

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	-0.04	0.08	-0.04	0.11	-0.05	0.19*	-0.09	0.02	0.09	0.38***	0.42***	1.63	0.10	0.00
	(-0.42)	(0.95)	(-0.27)	(1.17)	(-0.30)	(1.88)	(-0.83)	(0.17)	(0.95)	(2.91)	(2.64)			
β_{Mkt}	0.92***	0.97***	1.04***	0.98***	1.01***	0.92***	1.01***	1.01***	1.02***	0.96***	0.05			
β_{SMB}	-0.16**	0.08	0.03	0.10	0.06	-0.04	-0.16**	-0.07	-0.05	0.23***	0.39***			
β_{HML}	-0.20***	-0.18**	-0.17	-0.05	-0.09	0.06	-0.03	-0.05	-0.13**	0.01	0.21*			
β_{MOM}	0.04	0.00	0.06	-0.01	0.05	0.03	0.08***	0.06	-0.01	0.01	-0.03			
Adj. R^2	0.92	0.94	0.91	0.94	0.92	0.92	0.94	0.91	0.94	0.90	0.12			

Panel D: 5-Factor Regressions (Includes Quality Factor)

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	-0.01	0.11	0.02	0.17*	0.00	0.26**	-0.06	0.06	0.12	0.45***	0.46***	2.23	0.02	0.02
	(-0.06)	(1.27)	(0.15)	(1.79)	(-0.02)	(2.48)	(-0.53)	(0.56)	(1.58)	(4.03)	(2.83)			
β_{Mkt}	0.90***	0.96***	1.01***	0.94***	0.99***	0.88***	0.99***	0.99***	1.01***	0.92***	0.02			
β_{SMB}	-0.20***	0.05	-0.02	0.04	0.01	-0.11	-0.18**	-0.11	-0.08	0.15**	0.35***			
β_{HML}	-0.20***	-0.18**	-0.18*	-0.05	-0.09	0.05	-0.03	-0.05	-0.13*	0.00	0.20*			
β_{MOM}	0.05	0.01	0.08*	0.01	0.07*	0.05**	0.09***	0.08*	-0.01	0.03	-0.01			
β_{Q}	-0.12*	-0.11	-0.18	-0.20***	-0.16	-0.23***	-0.10	-0.14*	-0.10	-0.25	-0.14			
Adj. R^2	0.93	0.94	0.91	0.94	0.92	0.93	0.94	0.91	0.94	0.90	0.12			

the universe portfolio in terms of excess returns as the spread between the two end portfolios is not sufficiently large. In terms of the Sharpe ratio, the top-minus-bottom portfolio does perform better than the universe portfolio due to its volatility being much lower than that of the universe portfolio. Furthermore, substantial positive alphas that differ significantly from zero for the top and top-minus-bottom portfolios are observed for all three of the factor models. Again, a high positive alpha is generally observed on the top portfolio, but a distinct increasing pattern in alphas across the decile portfolios is not found. On the other hand, at a significance level of 5%, the GRS test on the five-factor alphas does indicate that these jointly differ from zero. This might still be partly attributable to the peculiar occurrence that the alphas of the fourth and sixth decile portfolios are positive and quite large in magnitude as compared to the alphas of the other portfolios. In the Cons test of Wolf and Romano (2013), these portfolios are not considered as I apply the test on the subset of the bottom portfolio and the top three portfolios. Within this subset, I find strongly significant *p*-values that reject the null hypothesis in favor of monotonically increasing patterns in alphas. Lastly, the addition of the quality factor tends to increase the alphas. The coefficients of the quality factor are generally negative and of similar order of magnitude across the decile portfolios, again rejecting the notion of these ES scores indicating similar information to the quality factor under its current definition.

Figure A8 and Table A14 in the appendix show the cumulative excess portfolios returns and the quantitative results of the regular global sorts. One may note that the outperformance (underperformance) of the top (bottom) portfolio is smaller than the sector-neutral counterpart result, leading to lower returns on the top-minus-bottom portfolio. Therefore, sector effects are present within the global sample. In all, I find that, in line with all previous results, the ES effect within the global sample is not attributable to the quality factor. Furthermore, Figures A9 and A10 in the appendix depict the cumulative excess returns for regular and sector-neutral North American portfolios, respectively. Tables A15 and A16 show the corresponding quantitative results. The ES premium is much less pronounced within the North American sample. The regular-sort top portfolio even underperforms the universe portfolio. However, positive excess returns are still observed on the top-minus bottom portfolios of the sector-neutral North American sorts. These returns are mainly attributable to the underperformance of the bottom portfolio. Distinction among levels of ES is thus still an effective aspect to consider in stock picking, although the regression results do not show alphas that differ significantly from zero, in a statistical sense. Furthermore, the negative exposures to the quality factor show that, also in North America, ES contains a different signal than quality under its current definition.

In all, high levels of employee satisfaction lead to higher stock returns than lower levels of employee satisfaction. This is particularly noticeable in Europe and on a global level, and less so in North America. The effect is not observed in a monotonic pattern when decile portfolios are formed on the basis of employee satisfaction, but a difference in stock returns between the two extreme-end portfolios is observed. The effect is found to be even stronger when industry/sector effects are controlled for. Furthermore, the observation of higher levels of employee satisfaction being associated with higher stock returns does not appear to be explicable by known factors, including the quality factor. Employee satisfaction is likely not caused by firm quality under its current definition, and its premium cannot be explained by the quality factor. Therefore, I can conclude that employee satisfaction has a relation to stock returns, albeit not a very strong one, and that this relation distinguishes itself from the relation between stock returns and quality.

6. EMPLOYEE SATISFACTION AND QUALITY

1. Quality Double Sorts

The above results suggest that the slight premium observed on the employee satisfaction score is a separate effect from the quality premium. To investigate this further, I also construct portfolios based on double quality-ES sorts. That is to say, I first sort the stocks in my universe into terciles according to their quality score, and then I sort the stocks within each tercile quality portfolio into quintile portfolios based on their ES score. I sort stocks into ES quintiles rather than into deciles as I wish to have at least 100 stocks in each double sorted portfolio. If I would sort the quality terciles into ES deciles, the resulting 30 portfolios will have less stocks and comparison of the portfolios to would lead to less clear distinctions between the portfolios if there are 30 of them. Furthermore, since the constituents of quality are measured on a quarterly basis, double sorted portfolios are updated four times a year, in contrast with the other sorts in this paper until now that have been performed on a yearly basis due to the ES scores being yearly data. I perform these double sorts for the constituent variables of quality separately, as well as the full quality score. I do this because while a control on quality as a whole might not eliminate the ES effect, it might be so that one of the individual measures is quite related to ES. Since the quality score is an average of the z-scores of its constituents, I perform the double sorts for the individual quality variables on the z-scores of these variables. One should note that since low accruals are desirable, I perform these sorts on the negative of the z-score of accruals which is also the manner in which accruals is incorporated into the total quality score. The average excess returns of the resulting 15 portfolios, as well as those of top-minus-bottom ES portfolios within each quality/quality constituent tercile, are shown in Table 10.

In accord with Kyosev (2013), a very strong quality effect is not observed in this sample. Namely, although the high quality portfolios generally have higher average returns than the low quality portfolios, the performance of mid-quality portfolios does not generally fall in between that of the low and high quality portfolios. This holds for both a double sort on the entire quality score and the double sorts on the individual quality variables and it can also be observed for the top-minus-bottom ES portfolios in the case of first sorting on the entire quality score, while we do not observe any quality effect in the top-minus-bottom ES portfolios when sorting on accruals and free cash flows to assets.

In terms of the ES effect, one may observe that, apart from a few irregular observations, there appears to be a near monotonic increase in average excess returns across the ES quintile portfolios (when moving from bottom to top ES) within the low and high quality stocks. As a completely monotonic increase in returns when sorting just on ES was not observed,

TABLE 10

Quality Double Sorted Portfolios

This table shows the average excess returns (in percentage terms) on value-weighted double sorted portfolios. Average excess returns are first calculated on a monthly basis and then annualized. Stocks are first sorted into terciles based on their negative accrual z-score, their free cash flows to assets z-score, their gross profit to assets z-score, and their quality score. Stocks are then sorted into quintile portfolios according to their ES scores within the accruals, free cash flows to assets, gross profit to assets, and quality terciles. Returns on these double sorted portfolios are available for the period of October 2003 - December 2015. Data on accruals, free cash flows to assets, and gross profit to assets have been obtained by matching the stocks in the CSA sample to the Robeco database. The quality score has been constructed, in the manner of Kyosev (2013), as an average of the z-scores of negative accruals, gross profits to assets, and free cash flows to assets.

		Employee Satisfaction					
		Bottom	P2	P3	P4	Top	Top-Bottom
Accruals	Low	6.06	8.91	9.72	9.67	10.74	4.44
	2	11.19	9.25	9.50	8.51	9.66	-1.39
	High	11.44	14.05	8.42	8.81	11.98	0.49
Free Cash Flows to Assets	Low	7.91	6.17	7.73	9.05	11.15	3.02
	2	7.81	9.39	10.17	10.59	6.80	-0.94
	High	11.14	9.70	11.46	10.13	12.45	1.19
Gross Profit to Assets	Low	7.82	7.36	8.66	7.42	6.08	-1.63
	2	10.59	10.23	11.00	10.89	10.85	0.24
	High	9.48	9.22	10.81	8.51	12.80	3.05
Quality	Low	5.97	12.16	6.88	8.05	8.78	2.66
	2	10.92	10.57	12.01	11.52	6.57	-3.95
	High	6.74	9.04	10.34	9.57	12.41	5.34

the effect that is observed within these quality terciles is in line with the earlier observed ES effect. Within the mid-quality stocks, an ES premium is not observed. A near monotonic increase of average excess returns with ES can be observed within the low accruals portfolios and within the low free cash flows portfolios. Furthermore, when first sorting on gross profit to assets, I notice a positive link between ES and average excess returns within the high gross profit to assets portfolios. Intuitively, the observation that an ES effect exists mainly in the low accruals and free cash flow portfolios, while within the gross profit to assets sorts it exists mainly within the high tercile portfolios, is in line with an ES effect existing mainly within low and high quality portfolios, which is what I find. In the end, since there is still some evidence for an ES premium within the low and high quality stocks, I again confirm that this slight ES advantage for stock returns persists when taking into account the quality of the stocks.

2. Testing the Employee Satisfaction Factor

Until now there has been little indication that the premium found on high ES stocks is attributable to the quality factor when considering the quality definition thus far applied in this paper. Therefore, I continue by further investigating this separate ES effect. In order to do so, I first form a factor based on the employee satisfaction scores. I construct the factor using the same method as the one used to construct the quality factor. Firstly, I divide stocks into large and small cap stocks and then sort the stocks within each of the two size divisions into terciles based on ES. The employee satisfaction

(ES) factor is then the average return on the value-weighted top-minus-bottom ES portfolios, as shown quantitatively below:

$$ES = \frac{1}{2}\ (Small\ High\ ES - Small\ Low\ ES) + \frac{1}{2}\ (Big\ High\ ES - Big\ Low\ ES) \tag{12}$$

I formally test whether the 5-factor model can be augmented with the ES factor, resulting in the model below:

$$R_{it} - R_{ft} = \propto_i + \beta_{MKT,i}(R_{MKT,t} - R_{ft}) + \beta_{HML,i}HML_t + \beta_{SMB,i}SMB_t + \beta_{MOM,i}MOM_t + \beta_{Q,i}Q_t + \beta_{ES,i}ES_t + \varepsilon_{it},$$
$$\varepsilon_{it} \sim NID(0, \sigma^2_{\varepsilon,i}) \tag{13}$$

I test whether this model can better explain stock returns than the equivalent five-factor model without the ES factor using a multivariate likelihood ratio test. I consider individual stock returns rather than portfolios, thereby going back to the base. In this test, I first regress the excess returns of each these stocks separately on the five factors and on the five factors plus the ES factor and posit the null hypothesis that the coefficients on the ES factor are jointly zero. The test statistic for this test is calculated as follows:

$$-\left[T - r - 1 - \frac{1}{2}(N - r + q + 1)\right] ln\left(\frac{|\widehat{\Sigma_0}|}{|\widehat{\Sigma_1}|}\right) \sim \chi^2_{p(r-p)} \tag{14}$$

where $\widehat{\Sigma_0}$ and $\widehat{\Sigma_1}$ are the estimated covariance matrices of the residuals resulting from the five-factor regression (null hypothesis) and six-factor regression (alternative hypothesis), respectively. T is the number of time observations (147) on each stock, r is the number of estimated coefficients under the alternative hypothesis, while q is the number of estimated coefficients under the null hypothesis. N is the number of stocks under consideration.

Since my sample of stocks is quite large (2828) stocks, applying this multivariate likelihood ratio test on the whole sample would render an invalid result as the covariance matrix of the error terms from the stocks would have a zero determinant. Therefore, I perform the test on random subsamples of 50 stocks in my sample and use cross-validation to confirm that the test conclusion remains the same across different subsamples. I cross-validate the above procedure for a total of 100 random subsamples and find that the null hypothesis, which implies the original factor model, is rejected at a significance level of 10% for only 2 these random subsamples. In fact, 86 out of the 100 subsamples result in a *p*-value above 0.99 and the average *p*-value among these 100 subsamples is 0.972. Therefore, I conclude that the addition of an ES factor to the five-factor model has little added value.

3. Quality-Plus

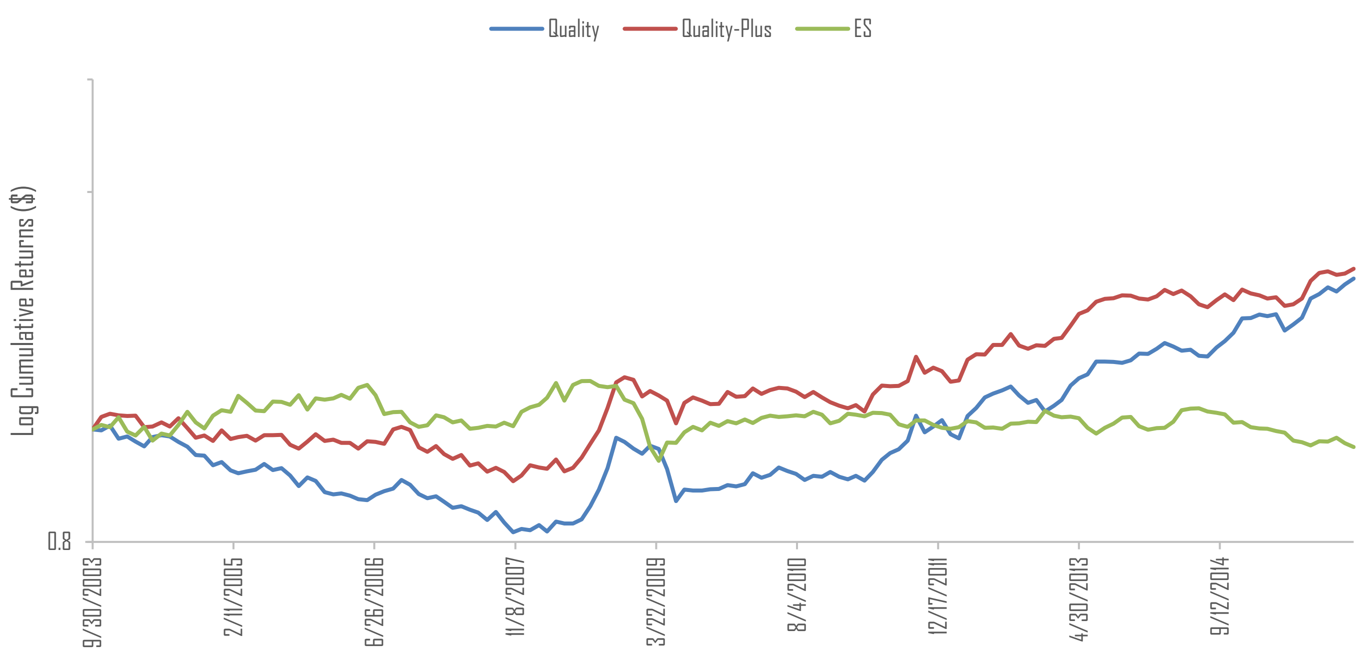
The above finding that the ES factor does not improve the five-factor model does not eliminate the possibility of ES being used to augment another factor. The ES factor has a negative Pearson's correlation coefficient of -0.165 with the quality factor and is thus quite a different factor. However, the employee satisfaction premium being a separate effect from the quality factor does not mean that the quality factor cannot be improved by including an employee satisfaction measure in its definition, in addition to its main constituents (accruals, gross profit to assets, and free cash flows to assets). In fact, from the double sorts it was observed that within high quality stocks, a return advantage is still to be gained from an ES strategy. Therefore, an ES screen as an additional signal for quality will likely provide fruitful investment results. Furthermore, the addition of ES to the quality factor might be especially relevant because the correlation between the quality and the ES factors is negative and thus the quality signal contained within ES is a different signal from the quality signal under quality's current definition. As mentioned previously, the definition of quality is still highly debated in academia and employee satisfaction could be considered as an additional pre-requisite for firm quality. Therefore, the addition of ES to the quality measure might lead to a multi-signal quality that is better at signaling firm quality than the plain quality measure.

Taking all of this into consideration, I construct the quality-plus factor which is constructed in exactly the same way as the quality factor, except that the quality score is augmented by the ES score. The quality-plus score is thus a simple average of the z-scores of (negative) accruals, gross profits to assets, free cash flows to assets, and the ES score. Figure 4 graphically depicts the compound cumulative returns on the quality factor, the ES factor, and the quality-plus factor for the global sample.

FIGURE 4

Factor Performance

This figure shows the cumulative compound returns of 1 dollar being invested in the quality-plus, quality, and employee satisfaction (ES) factors at the end of September 2003. The ES factor is re-balanced on a yearly basis, while the quality and quality-plus factors are re-balanced on a quarterly basis. Factor portfolios are held until December 2015. Factors are constructed on a value-weighted basis. The cumulative compound returns are calculated as $(1+r_1)(1+r_2)\ .\ .\ .(1+\ r_T)$. The graph is plotted on a logarithmic scale with base 5.



The ES factor performs better than the other two factors in the beginning of the sample period, but its performance deteriorates in the second half of the sample period. As expected the cumulative returns on the quality and the quality-plus factors follow a similar pattern, however the quality-plus factor performs slightly better than the quality factor over this sample (period). The distance between the cumulative performances of the two factors decreases near the end of the sample period as the performance of the quality factor is increasing more steeply. This is in line with the finding of Kyosev (2013) who finds that the quality factor is less dominant during the period of 2003 until 2012.

The difference between the two quality factors appears to be quite small in Figure 4. However, it is prudent to check whether a 5-factor model that includes Carhart's four factors and the quality factor better explains stock returns than the corresponding model with the quality-plus factor. Rather than focusing on value-weighted portfolios of stocks, I want to test this at the base: the stock returns of the individual stocks in my sample. I want to examine which of these two five-factor models best models the stock returns in my sample. I posit a null hypothesis of the two models performing equivalently versus an alternative hypothesis of the model with the quality-plus factor performing better. To my knowledge there is not a widely-used test that tests non-nested hypotheses over a large sample of dependent variables simultaneously. Therefore, I consider an approximation that makes use of the sum of squared residuals. Using each of the two factor models, I regress excess returns for each of the stocks on the two factor models. For each stock, I calculate the sum of squared residuals for each of the two factor models and I construct the following test statistic for stock i:

$$d_i = \frac{SSE_{i,Q} - SSE_{i,PLUS}}{SSE_{i,PLUS}} \tag{15}$$

where $SSE_{i,Q}$ and $SSE_{i,PLUS}$ are the sum of squared residuals resulting from a regression of stock i's excess stock returns on the model with the quality factor and the model with the quality-plus factor, respectively. A large value of d_i then indicates that the new model better explains the stock returns of stock i than the original model. My null and alternative hypotheses in terms of d_i are thus:

$$H_0: d_i = 0 \qquad vs. \qquad H_a:\ d_i > 0 \tag{16}$$

For each stock, I simulate a critical value distribution under the null hypothesis to compare to these test statistics to. Therefore, I create some null-enforced excess return series by regressing all excess stock returns on the original model and subtracting the residual, replacing it with a residual drawn from a normal distribution with the same variance as the original residuals. I then re-sample from this null-enforced data as described in the algorithm below. Re-sampling is done using a moving block bootstrap with a block length of 12 months, allowing for overlap between blocks.

- For stock i, draw 5 moving blocks from the null-enforced excess return series, resulting in 60 bootstrap observations
- Calculate d_i* using equation 15

- Repeat these steps 1000 times, resulting in statistics $d_1{*}$, $d_2{*}$, . . . , $d_{1000}{*}$
- The distribution of $d_{i,1}{*}$, $d_{i,2}{*}$, . . . , $d_{i,1000}{*}$ is then the bootstrap approximation for the sampling distribution of test statistic d_i under the null hypothesis
- Calculate the p-value of d_i for the one-sided alternative hypothesis of $d_i > 0$
- Repeat for all stocks $i = 1, 2, \ldots, 2828$, resulting in a p-value per stock.

I find that the average p-value among the stocks in my sample is 0.06 and the variance of the p-values is 0.02. Furthermore, for 62.9% of the stocks in my sample the null hypothesis is rejected in favor of the alternative hypothesis at a significance level of 1%. This value is 78.6% when considering a significance level of 10%. I can thus safely conclude that a five-factor model that includes the quality-plus factor is better at explaining the excess returns of the stocks in my sample than a five-factor model that includes the original quality factor.

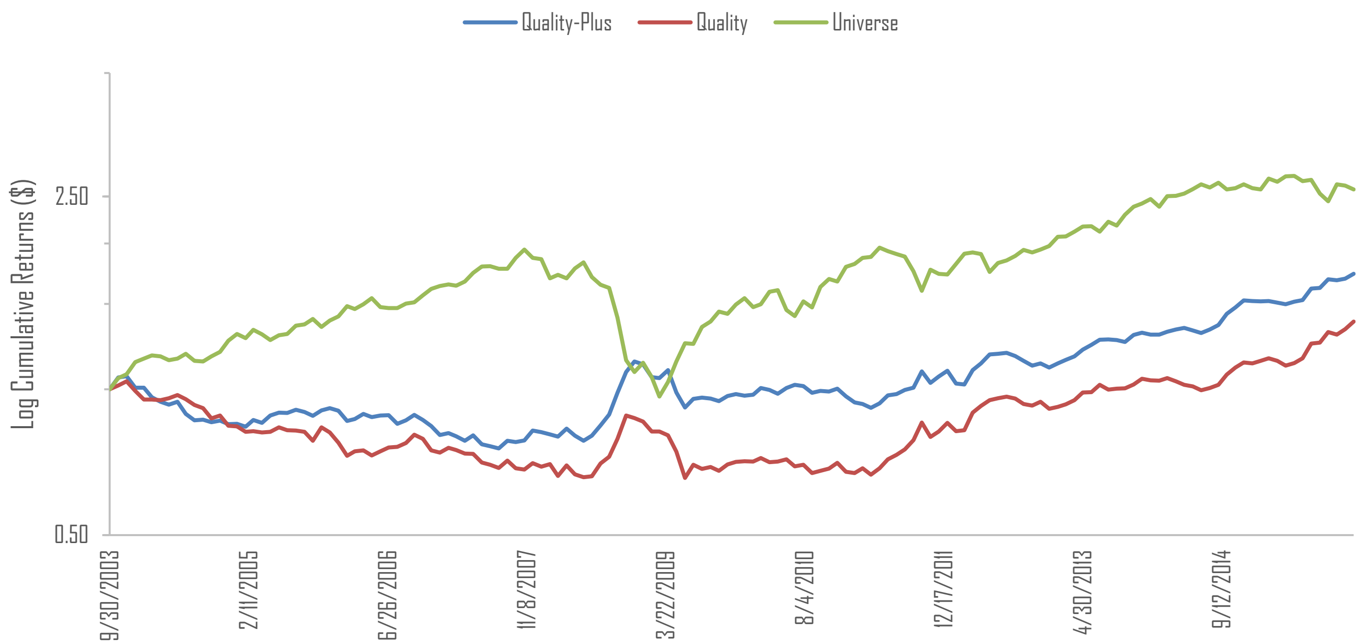
Since the quality-plus factor, the quality factor augmented by ES scores, is found to be a better fit in the five-factor model than the original quality factor, I now analyze the performance of quality-plus and quality sorts side by side. I do this by again constructing decile portfolios by sorting on the quality-plus score and by sorting on the quality score. Figure 5 graphically depicts the cumulative compound excess return of value-weighted long-short portfolios constructed by going long in the top decile of the sorted stocks and short in the bottom decile of the sorted stocks.

Again, unsurprisingly for this sample period, both portfolios underperform the universe portfolio. Since I want to compare the quality-plus sorts to the quality sorts, the latter of which is known to perform much better in other sample periods, I compare these two to each other. One may note that the quality-plus portfolio outperforms the quality portfolio. Table 11 quantitatively shows the performance measures of these decile portfolios based on the quality-plus and quality scores and the corresponding results from CAPM and Carhart's four-factor regressions. Panels A and B show the performance measures of the quality-plus and quality portfolios, respectively, and Panels C and D show the alphas, their t-statistics, and the adjusted R-squared values from the regressions. The top and top-minus-bottom quality-plus portfolios have a higher Sharpe ratio than the corresponding quality portfolios. However, the superior average excess returns of the top-minus-bottom quality-plus portfolio (as compared to the top-minus-bottom quality portfolio) originate mainly from shorting the bottom portfolio, which has quite lower returns than that of the regular quality sort. Neither of the average excess returns series follow a distinct monotonic increasing pattern across the decile portfolios. The alphas behave in a similar way. The top and top-minus-bottom portfolios of the quality-plus sorts outperform those of the quality sorts, while the bottom portfolio of quality-plus underperforms that of quality. However, in terms of statistical significance, the bottom, top and top-minus-bottom quality-plus alphas differ significantly from zero whereas for the quality sorts statistical significance of the alphas is mainly observed in the mid and mid-upper quality portfolios, and the top-minus-bottom quality portfolio. So, an effect of high quality is present also for the mid-upper decile portfolios, although this effect is

FIGURE 5

Performance Long-Short Portfolios

This figure depicts the cumulative compound returns of value-weighted long-short portfolios constructed on the basis of quality and quality-plus scores. Stocks are sorted into deciles according to their quality and quality-plus scores and long-short portfolios are formed by going long in the highest quality(-plus) decile and short in the lowest quality(-plus) decile. These are the cumulative returns of 1 dollar being invested in the long-short portfolio at the end of September 2003. Portfolios are re-balanced on a quarterly basis and held until December 2015. Universe is the value-weighted portfolio of all stocks in the entire CSA universe. The cumulative compound returns are calculated as $(1+r_1)(1+r_2)\,.\;\;.\;\;.(1+\;r_T)$. The graph is plotted on a logarithmic scale with base 5.



not increasing when moving along the decile portfolios. Furthermore, the test of Wolf and Romano (2013) on the subset of the bottom and the top three decile alphas does not indicate a monotonic increase in alphas for neither the quality nor the quality-plus sorts. However, the *p*-value of this test is pointedly lower for the quality-plus sorts, as compared to that of the quality sorts. This does suggest that for this sample period, stock portfolio allocation on the basis of the quality-plus score will be more fruitful than allocation on the basis of the quality score.

TABLE 11

Factor-Adjusted Returns of Global Quality-Plus and Quality Decile Portfolios

This table presents performance measures and regression results of global value-weighted decile portfolios, sorted on quality-plus and quality. Bottom contains the stocks with lowest quality(-plus) scores, Top contains highest quality(-plus) score stocks. Universe is the value-weighted portfolio of all stocks in the CSA universe. Portfolio returns are available for October 2003 - December 2015. Panels A and B show annual performance measures of the quality-plus decile portfolios and the quality decile portfolios, respectively. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels C and D show the regression results of the CAPM and 4-factor regressions for the quality-plus decile portfolios and the quality decile portfolios, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, and the momentum (MOM) factor. α is the regression intercept. The returns on the global Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding p-value, and the p-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures Quality-Plus													
	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	4.40	7.82	6.93	6.46	6.56	8.15	9.50	9.05	9.02	9.78	5.18	9.29		0.51
Volatility	18.03	15.68	16.96	17.99	14.88	15.81	14.64	14.30	14.32	13.05	10.70	14.99		
Sharpe	0.24	0.50	0.41	0.36	0.44	0.52	0.65	0.63	0.63	0.75	0.48	0.62		
Panel B: Performance Measures Quality													
	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	6.35	7.30	8.22	9.44	10.25	8.37	11.06	10.34	10.14	9.89	3.35	9.29		0.54
Volatility	20.65	17.09	16.54	16.74	16.64	16.79	15.47	14.25	13.05	14.21	11.61	14.99		
Sharpe	0.31	0.43	0.50	0.56	0.62	0.50	0.71	0.73	0.78	0.70	0.29	0.62		
Panel C: Factor Regressions Quality-Plus													
	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
1-F α	-0.34**	0.02	-0.10	-0.18*	-0.05	0.03	0.20	0.17	0.16	0.29***	0.63***	1.34	0.22	0.63
	(-2.14)	(0.14)	(-0.62)	(-1.97)	(-0.44)	(0.27)	(1.27)	(1.43)	(1.06)	(2.72)	(2.76)			
Adj. R^2	0.88	0.88	0.89	0.90	0.89	0.91	0.85	0.88	0.89	0.83	0.21			
4-F α	-0.25*	0.02	-0.17	-0.13	-0.13	-0.04	0.22	0.17*	0.17	0.25***	0.50**	1.51	0.14	0.19
	(-1.69)	(0.12)	(-1.01)	(-1.18)	(-1.17)	(-0.33)	(1.41)	(1.74)	(1.60)	(2.69)	(2.10)			
Adj. R^2	0.89	0.87	0.89	0.90	0.90	0.92	0.86	0.90	0.90	0.86	0.35			
Panel D: Factor Regressions Quality													
	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
1-F α	-0.27	-0.09	0.00	0.08	0.14*	0.00	0.26**	0.25***	0.30**	0.24*	0.51*	2.17	0.02	1.00
	(-1.25)	(-0.50)	(-0.04)	(0.84)	(1.69)	(-0.02)	(2.51)	(2.93)	(2.38)	(1.97)	(1.85)			
Adj. R^2	0.85	0.91	0.94	0.94	0.95	0.94	0.92	0.94	0.89	0.87	0.24			
4-F α	-0.21	-0.09	-0.01	0.06	0.11	-0.05	0.27***	0.25***	0.23**	0.24**	0.44*	2.29	0.02	0.91
	(-1.14)	(-0.53)	(-0.15)	(0.65)	(1.35)	(-0.56)	(2.65)	(3.17)	(2.48)	(2.19)	(1.91)			
Adj. R^2	0.87	0.91	0.94	0.94	0.95	0.94	0.93	0.95	0.91	0.90	0.33			

7. DISSECTING QUALITY-PLUS

1. METHODOLOGY: FAMA-MACBETH REGRESSIONS

While the above portfolio regressions and corresponding tests can provide an answer to the question whether there exists a return premium due to the quality-plus score which cannot be attributed to the size, value, and momentum factors, it does not show the marginal effect of the quality-plus factor on stock returns. Such marginal effects can be examined with Fama-MacBeth (1973) analysis. The Fama-MacBeth procedure is a two-step procedure. The first step constitutes time-series regressions of the excess returns of each of the stocks in my sample on the factors under consideration. This regression, which is done separately for each stock, can be expressed quantitatively as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{Plus,i} QPlus_t + \boldsymbol{F_t \beta_{F,i}} + \varepsilon_{i,t} \quad , \quad \varepsilon_{it} \sim NID(0, \sigma^2_{\varepsilon,i}) \tag{17}$$

where $R_{it} - R_{ft}$ is again the monthly return in excess of the risk-free rate of stock i at time t. Furthermore, $QPlus_t$ denotes the return on the quality-plus factor at time t and $\beta_{Plus,i}$ is stock i's coefficient on the quality-plus factor. $\boldsymbol{F_t}$ is a matrix of time t observations on other factors considered in the procedure, while $\boldsymbol{\beta_{F,i}}$ is a vector of stock i's coefficients on those factors. I apply the procedure in three versions, each time varying the factors included in $\boldsymbol{F_t}$. In the first version, $\boldsymbol{F_t}$ is left empty and the stock returns are only regressed on a constant and the quality-plus factor. In the second version, $\boldsymbol{F_t}$ includes only the market factor, while I add the size, value, and momentum factors in the third version. Lastly, α_i is the intercept for stock i and $\varepsilon_{i,t}$ denotes the error term. In this first step I thus obtain coefficient estimates on the factors for each stock in the CSA sample.

The second step of the Fama-MacBeth procedure consists of cross-sectional regressions in which one regresses the excess stock returns of all stocks in the sample at each point in time on the factor betas obtained from the regressions in equation 17. In fact, for each time t, the following regression is performed:

$$R_{it} - R_{ft} = \alpha_t + \lambda_{Plus,t} \hat{\beta}_{Plus,i} + \boldsymbol{\hat{\beta}'_{F,i} \lambda_{F,t}} + \varepsilon_{t,i} \quad , \quad \varepsilon_{it} \sim NID(0, \sigma^2_{\varepsilon,t}) \tag{18}$$

Again $R_{it} - R_{ft}$ denotes the monthly excess returns of stock i at time t, $\hat{\beta}_{Plus,i}$ and $\boldsymbol{\hat{\beta}_{F,i}}$ are the beta-estimates on the quality-plus factor and the other set of factors obtained from performing the time-series regression in equation 17 for stock i. $\lambda_{Plus,t}$ and $\boldsymbol{\lambda_{F,t}}$ are their corresponding premia estimates. Lastly, α_t signifies the intercept of the time t regression and $\varepsilon_{t,i}$ again denotes the error term. Inferences are then made on the over-time-mean values of α_t, $\lambda_{Plus,t}$, and $\boldsymbol{\lambda_{F,t}}$.

I apply the overall procedure using the quality-plus factor as the main factor under investigation, however I also investigate the quality and the ES factors separately. I do this by replacing $QPlus_t$ by ES_t or by Q_t in equation 17, the employee satisfaction and the quality factor, respectively. Consequently, the beta-estimates for the quality-plus factor in equation 18 are replaced by beta estimates on the quality factor and the ES factor. I do this because if either quality or the ES factor is the driving force behind a quality-plus premium, this might not show in a regression on the quality-plus beta. In fact, Novy-Marx (2016) shows that back-tests of multi-signal strategies suffer from overfitting bias. As the quality-plus factor is a multi-signal strategy, this research might also hold vice versa: a quality-plus alpha may persist in the presence of the other factors, however, this may be the 'quality alpha' or the 'ES alpha'.

In the past, the Fama-MacBeth procedure has been widely accepted and used to establish a relationship between portfolio returns and economic factors. However, recently academics have questioned the validity of this procedure. I still make use of the procedure in this paper, however I consider some adaptions to the procedure. Firstly, Kleibergen and Zhan (2015) find that when observed proxies for unobserved true factors are only marginally correlated, there remains a large unexplained factor structure in the first pass regression residuals. This has consequences for the validity of the *R*-squared value and the *t*-statistics from the second pass regression. In fact, values for the *R*-squared statistic are large due to the unexplained factor structure in the first regression residuals, yet Kleibergen and Zhan (2015) demonstrate that these *R*-squared values have a large random component. This results in a large estimation error in the first regression beta, which is also included as an explanatory variable in the second regression. Therefore, one might wrongly conclude that there is a lot of explanatory power in the independent variables in the second regression. Furthermore, in this case, the limiting distribution of the *t*-statistic also does not apply, rendering the *t*-test useless. To allow for a better interpretation of the obtained *R*-squared values and *t*-statistics, I also report the unexplained factor structure in the residuals of the first pass regression. I do so using the FACCHECK measure of Kleibergen and Zhan (2015). A scree plot shows that most of the variability in the excess return sample of the stocks in the sample can be explained by the first three principal components (when applying eigenvalue decomposition on the covariance matrix), thus indicating that the excess returns have a factor structure of three factors. The FACCHECK measure is then the percentage of variation in the first pass regression residuals that is explained by the first three principal components of the covariance matrix of the residuals. The measure thus checks how much of the factor variation is collected in the residuals after performing regression 17. The FACCHECK measure is thus calculated as follows:

$$FACCHECK = \frac{\lambda_1 + \lambda_2 + \lambda_3}{\sum_{i=1}^{N} \lambda_i} \tag{19}$$

where λ_i is the eigenvalue corresponding the ith principal component of the covariance matrix of the first pass residuals and N is the total number of principal components in this covariance matrix i.e. the number of time-series of residuals or the number of stocks in the universe under consideration. A small FACCHECK value indicates little unexplained factor structure in the residuals, hence the interpretation of the regression coefficients and statistics can proceed as usual. On the other hand, a large FACCHECK value means that statistics are biased and caution should be taken with their interpretation. In their paper, Kleibergen and Zhan (2015) use a rule of thumb to decide whether a calculated FACCHECK value is so large that unexplained factor structure in the residuals is problematic. However, this rule of thumb is particular to the dataset that they consider. Therefore, in order to make an inference on whether a FACCHECK value indicates significant unexplained residual factor structure, a relevant distribution that can be used for the calculation of a *p*-value for this

FACCHECK value would be utmost useful. I simulate such a distribution under the null hypothesis of no factor structure in the first pass residuals. The following algorithm describes this simulation:

- For each point in time t (with $t = 1,2 \ldots, T$), draw a set of N residuals from normal distribution $N(0, \hat{\Sigma})$ where $\hat{\Sigma} = \begin{pmatrix} \hat{\sigma}^2_{\varepsilon,1} & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \hat{\sigma}^2_{\varepsilon,N} \end{pmatrix}$ with $\sigma^2_{\varepsilon,i}$ the sample variance estimate of the residuals of the first pass regression for stock i and N the number of stocks in the sample
- Calculate the covariance matrix of this $T \times N$ residual matrix
- Compute the principal components and their corresponding eigenvalues of this covariance matrix
- Calculate the FACCHECK measure using the formula in equation 19
- Repeat the above steps 1000 times and obtain a set of FACCHECK values: $\{FACCHECK^*_1, FACCHECK^*_2, \quad . \; . \; . \quad , FACCHECK^*_{1000}\}$
- This set of FACCHECK values serves as an approximation to the theoretical distribution of FACCHECK under the null hypothesis of no unexplained factor structure in the residuals (i.e. $H_0: FACCHECK = 0$ vs. $H_a: FACCHECK > 0$) and this distribution is then used to calculate a *p*-value for the empirical FACCHECK value

One should note that I consider $\hat{\Sigma}$ as a diagonal matrix, disregarding any covariance between the residuals of different stocks. I do this in order to ensure that these residuals under the null hypothesis do not contain any unexplained factor structure at all. For each of the Fama-MacBeth procedures I apply, I also report the FACCHECK value of the first pass regression, as well as its corresponding *p*-value. A large FACCHECK value leads to a small *p*-value, rejecting the null hypothesis of no unexplained factor structure in favor of the alternative hypothesis that there is unexplained factor structure present in the first pass residuals.

In case of a large FACCHECK value and subsequently biased statistics, one possible solution is to replace the regular Fama-MacBeth procedure by the Pen-FM procedure of Bryzgalova (2014). The first step of the Pen-FM procedure is identical to that of the Fama-MacBeth procedure, but the second regression is augmented by a penalty term in its loss function. This penalty term is inversely proportional to the strength of the factors and will shrink the coefficients of irrelevant factors towards zero. The procedure thereby identifies the irrelevant factors. This responds exactly to the problem of observed proxies for unobserved true factors only being marginally correlated with these true factors that Kleibergen and Zhan (2015) identify as the cause for unexplained first pass residual factor structure. The Pen-FM procedure thus eliminates the need to investigate these biased *R*-squared values and *t*-statistics separately, as it provides robust, unbiased *R*-squared values and stipulates the use of a more sound inference method than these biased *t*-tests. I outline this inference method later on in this section. Furthermore, as the Pen-FM procedure identifies irrelevant factors, it not only identifies those factors that proxy a specific unobserved factor but do so badly, but it also identifies factors which are not a proxy for any of the unobserved factors at all. In the latter case, it might be so that all unobserved factors are adequately proxied by the factors in a factor model, yet the factor model also includes an additional irrelevant factor. This will not lead to unexplained factor structure in the residuals of the first pass regression and thus cannot be observed the FAC-CHECK measure. Yet, since my aim is to investigate the marginal factor effects of the factors, the identification of such useless factors is quite relevant and the Pen-FM procedure better facilitates such identification than the regular Fama-MacBeth procedure. Therefore, it is prudent to replace the second step in the Fama-MacBeth procedure with that of the Pen-FM procedure in all cases, regardless of whether there exists unexplained factor structure in the first pass residuals which is exactly how I proceed in this paper.

As mentioned, the Pen-FM procedure works by augmenting the regular least squares loss function used to estimate the premia ($\lambda_{Plus,t}$ and $\boldsymbol{\lambda_{F,t}}$), in equation 18, with a penalty term. The loss function under consideration looks as follows:

$$\boldsymbol{\hat{\lambda}_{pen}} = min_{\lambda} \left[\boldsymbol{\bar{R}} - \ \boldsymbol{\hat{\beta}}'\boldsymbol{\lambda} \right]' \left[\boldsymbol{\bar{R}} - \ \boldsymbol{\hat{\beta}}'\boldsymbol{\lambda} \right] + \ \eta_{\boldsymbol{T}} \ \sum_{j=1}^{K} \frac{1}{\|\boldsymbol{\hat{\beta}_j}\|_{\boldsymbol{1}}^{d}} \left|\lambda_{\boldsymbol{j}}\right| \tag{20}$$

where $\boldsymbol{\lambda} = [\alpha \quad \lambda_{Plus} \quad \boldsymbol{\lambda_F}]'$ are the intercept and the premia under investigation for the $K-1$ factors under consideration. $\boldsymbol{\bar{R}}$ is a $N \times 1$ vector constituting the over-time mean values of excess returns on the N stocks under consideration, while $\boldsymbol{\hat{\beta}}$ is a $K \times N$ matrix of estimated beta coefficients on the $K-1$ factors for each of the N stocks in the time-series regressions of equation 17. The first column of $\boldsymbol{\hat{\beta}}$ constitutes vector $\boldsymbol{\iota_N}$, a $N \times 1$ vector of ones. $\eta_{\boldsymbol{T}} > 0$ and $d > 0$ are tuning parameters which I set to 4 and $\bar{\sigma}$, respectively. $\bar{\sigma}$ is the average standard deviation of the residuals from the first pass regression and I follow Bryzgalova (2014) in these settings as she shows that the impact of the choice of tuning parameter on the functioning of the Pen-FM of is negligible. Lastly, $\|\boldsymbol{\hat{\beta}_j}\|_{\boldsymbol{1}}$ is the L1-norm of the jth row of $\boldsymbol{\hat{\beta}}$. That is, $\|\boldsymbol{\hat{\beta}_j}\|_{\boldsymbol{1}} = \ \boldsymbol{\hat{\beta}_j}\boldsymbol{\iota_N}$.

In this case, the $\boldsymbol{\lambda}$ estimates are obtained by minimizing equation 20 directly (rather than looking at the over-time mean as in equation 18) as I consider a cross-sectional regression of the over-time mean excess returns rather than a cross sectional regression at each point in time. The solution to the loss function in equation 20 thus provides an estimate for $\boldsymbol{\lambda}$ in the following regression:

$$\boldsymbol{\bar{R}} = \boldsymbol{\hat{\beta}}'\boldsymbol{\lambda} \ + \ \boldsymbol{\varepsilon}, \quad with \quad \boldsymbol{\varepsilon} = \begin{bmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_N \end{bmatrix} \ , \qquad\qquad \varepsilon_i \sim NID(0, \sigma_{\varepsilon}^2) \tag{21}$$

When the Pen-FM procedure is applied to more than one factor, there is no analytical solution to the minimization problem in equation 20. Following Bryzgalova (2014), I thus derive $\boldsymbol{\hat{\lambda}_{pen}}$ numerically using the pathwise coordinate descent algorithm which updates only one parameter estimate at the time. Algorithm A2 in Appendix A5 outlines this procedure. This algorithm results in an estimate $\boldsymbol{\hat{\lambda}_{pen}}$. In order to make any inferences about these premia estimates, I calculate the following test statistic:

$$\boldsymbol{B_T} = \ \sqrt{T} \left(\boldsymbol{\hat{\lambda}_{pen}} - \ \boldsymbol{\lambda_0} \right) \tag{22}$$

where T is the number of month observations in the sample and $\boldsymbol{\lambda_0}$ is the parameter under the null hypothesis. Since I want to test whether the premia and the intercept significantly differ from zero, this results in $\boldsymbol{\lambda_0} = \mathbf{0}_{\boldsymbol{K}}$.

Furthermore, a theoretical distribution to compare this test statistic to is required. I again follow Bryzgalova (2014) in the use of a bootstrap procedure to obtain such a distribution. The procedure for this bootstrap is outlined in Algorithm A3 in Appendix A5. Next to the coefficient estimates and their corresponding *p*-values, I also report the *R*-squared of the second pass regression as well as the shrinkage rate of the factor under investigation. The *R*-squared value is calculated in its conventional manner:

$$R^2 = 1 - \frac{\left[\left[\bar{\boldsymbol{R}} - \hat{\boldsymbol{\beta}}\prime\hat{\boldsymbol{\lambda}}_{\boldsymbol{pen}}\right]'\left[\bar{\boldsymbol{R}} - \hat{\boldsymbol{\beta}}\prime\hat{\boldsymbol{\lambda}}_{\boldsymbol{pen}}\right]\right]}{\left[\bar{\boldsymbol{R}} - \left(\frac{\bar{\boldsymbol{R}}\prime\boldsymbol{\iota_N}}{N}\right)\boldsymbol{\iota_N}\right]'\left[\bar{\boldsymbol{R}} - \left(\frac{\bar{\boldsymbol{R}}\prime\boldsymbol{\iota_N}}{N}\right)\boldsymbol{\iota_N}\right]} \tag{23}$$

Lastly, the shrinkage rate is the percentage of times that a coefficient is set to exactly zero by the Pen-FM procedure during the bootstrap simulations.

2. The Marginal Effect of Quality-Plus

As mentioned, the Fama-MacBeth procedure is used to separate the marginal effects of factors and to estimate their true premia. Table 12 shows the results of the Pen-FM procedure. Panel A considers only the factor under investigation (Quality-Plus, Quality, ES, or the combination of Quality and ES), Panel B adds the market factor in both of the regression steps of the procedure. Panel C augments the regressions from Panel B with the size (SMB) factor, value (HML) factor, and momentum (MOM) factor. The table shows the coefficient estimates from the Pen-FM second pass regression, as well as their *p*-values. Furthermore, the table also reports the shrinkage rate for each of the factors in the regressions, the FACCHECK measure for unexplained factor structure in the first pass residuals, the *R*-squared value of the second step of the procedure, and the number of stocks considered in the second regression. This number is a bit smaller than the number of stocks in the entire sample as some stocks had quite some missing observations in their time-series, invalidating the first step per-stock time-series regression of the procedure (in comparison to previous analysis in which portfolios were formed and thus the stocks could be incorporated into that analysis for those time periods that return and market capitalization observations were available).

Panel A shows that the quality-plus, quality, and ES factors have negative premiums, although these are not significantly different from zero in a statistical sense. One should keep in mind that the ES effect was shown not to be linearly related to stock returns across all levels of ES and that the quality factor does not perform as well in this sample as it does in other samples. These two occurrences are likely the explanation for these negative premiums. The premium on quality-plus is a bit larger in absolute magnitude than that of the separate quality and ES factors, as well as the coefficients on these factor betas when both the quality and ES factors are included in the regressions.

TABLE 12

Pen-FM Results

This table presents the results of the Pen-FM procedure. The rows indicate the main factor under investigation: quality-plus (Q-Plus), quality (Q), employee satisfaction (ES), or ES and Q simultaneously, while the columns contain the premia on all factors in the regressions. Monthly excess returns over the sample period of October 2003 - December 2015 are used in the regressions. *p*-values are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. Panel A shows the results when only the factor(s) being tested is included in the procedure. Panel B adds the market factor (MKT) to the regressions, and Panel C further adds the size (SMB) factor, the value (HML) factor, and the momentum (MOM) factor. The table also shows the premium shrinkage for each of the factors, the FACCHECK (FC) measure for unexplained factor structure in the first-pass residuals, and the *p*-value of this FACCHECK value. Lastly, it shows the *R*-squared of the second-pass regression and the number of stocks used in this cross-sectional regression.

					Panel A: 1-Factor Pen-FM							
	Intercept	Q-Plus	Q	ES	MKT	SMB	HML	MOM	FACCHECK	*p*-value	R^2	# Obs
Q-Plus	1.03*	-0.18							0.25	0.00	0.05	2675
	(0.09)	(0.25)										
Shrinkage	0	0.00										
Q	1.02*		-0.14						0.21	0.00	0.04	2675
	(0.09)		(0.25)									
Shrinkage	0		0.00									
ES	1.33**			-0.03					0.29	0.00	0.00	2675
	(0.03)			(0.25)								
Shrinkage	0			0.00								
ES + Q	1.08*		-0.14	-0.13					0.21	0.00	0.06	2675
	(0.08)		(0.25)	(0.25)								
Shrinkage	0		0	0.00								
					Panel B: 2-Factor Pen-FM							
	Intercept	Q-Plus	Q	ES	MKT	SMB	HML	MOM	FACCHECK	*p*-value	R^2	# Obs
Q-Plus	1.06*	-0.19			0.16***				0.10	0.08	0.05	2675
	(0.07)	(0.25)			(0.00)							
Shrinkage	0	0			0							
Q	1.08*		-0.15		0.14***				0.10	0.28	0.04	2675
	(0.06)		(0.25)		(0.00)							
Shrinkage	0		0		0							
ES	0.99*			-0.12	0.29***				0.12	0.00	0.03	2675
	(0.09)			(0.25)	(0.00)							
Shrinkage	0			0	0							
ES + Q	1.07*		-0.14	-0.13	0.15***				0.10	0.27	0.06	2675
	(0.06)		(0.25)	(0.25)	(0.00)							
Shrinkage	0		0	0.00	0							
					Panel C: 5-Factor Pen-FM							
	Intercept	Q-Plus	Q	ES	MKT	SMB	HML	MOM	FACHECK	*p*-value	R^2	# Obs
Q-Plus	0.89	-0.15			0.29***	0.20***	-0.34	0.16***	0.10	0.22	0.12	2675
	(0.12)	(0.25)			(0.00)	(0.00)	(0.24)	(0.00)				
Shrinkage	0	0			0	0	0	0				
Q	0.90		-0.10		0.28***	0.19***	-0.34	0.16***	0.09	0.53	0.12	2675
	(0.12)		(0.24)		(0.00)	(0.00)	(0.25)	(0.00)				
Shrinkage	0		0		0	0	0	0				
ES	0.88			-0.10	0.30***	0.20***	-0.34	0.17***	0.11	0.04	0.12	2675
	(0.12)			(0.25)	(0.00)	(0.00)	(0.23)	(0.00)				
Shrinkage	0			0		0	0	0				
ES + Q	0.90		-0.10	-0.11	0.27***	0.19***	-0.33	0.15***	0.09	0.50	0.12	2675
	(0.12)		(0.25)	(0.26)	(0.00)	(0.00)	(0.26)	(0.00)				
Shrinkage	0		0	0	0	0	0	0				

Furthermore, although the coefficients on these factor betas do not differ significantly from zero, the shrinkage rate of these coefficient is equal to zero. The Pen-FM procedure thus does identify these factors as relevant factors and does not eliminate them, suggesting that, although they have a small negative premium, a measure of quality or ES is a useful addition to a factor model. Panel B shows that these premiums behave in a similar way in the presence of the market factor. The factor premia are again negative and of similar magnitude. One exception is the estimated premium on the ES factor which grows more negative in the presence of the market factor. These premia again do not differ significantly from zero, but the shrinkage rates are zero. The interpretations of the premia estimates are similar in the presence of the size, value, and momentum factors to when just the market factor is included in the regression. In fact, $\hat{\lambda}_{Plus}$, $\hat{\lambda}_{Q}$, and $\hat{\lambda}_{ES}$ are again all negative, yet not statistically different from zero. Again, the Pen-FM procedure does not identify these factors as completely irrelevant as shrinkage rates are zero for these regressions as well. However, one may notice a slight decline in the absolute values of $\hat{\lambda}_{Plus}$, $\hat{\lambda}_{Q}$, and $\hat{\lambda}_{ES}$ when the other factors are included in the regressions. The marginal effect of quality-plus and its constituents on stock returns is thus more favourable in the presence of other factors. Furthermore, the one-factor and two-factor Pen-FM procedure results in intercept estimates, around the value of one, that differ significantly from zero at the 10% significance level, whereas these intercepts are slightly lower and insignificant in the 5-factor Pen-FM procedure as the marginal effects of these additional factors account for a larger proportion of the stock returns.

One may observe that stock returns load considerably positively on the market beta. In all regressions its coefficient differs significantly from zero at the 1% statistical significance level. The market premium in the presence of the betas of other known factors, rather than just in the presence of the quality-plus, quality, and ES factor betas, is higher. Furthermore, stock returns also tend to have an economically significant simultaneous size and momentum premium. Exposure to these betas is positive and differs significantly from zero at the 1% statistical significance level. However, for the stocks in this sample over the sample period of 2003-2015, there appears to be a negative value premium. This premium does not differ significantly from zero, even at the 10% statistical significance level, yet the Pen-FM procedure does not identify the value factor as a useless factor as is demonstrated by the shrinkage rate.

In addition, the explanatory power of the second step in the Pen-FM procedure is higher when all factors are included. One should note that, following Bryzgalova's (2014) manner of reporting, I report the *R*-squared value here, rather than the adjusted *R*-squared measure. It is thus not unsurprising that the *R*-squared value increases in the number of independent variables, although the *R*-squared values are nearly the same between the one-factor and two-factor regressions. On the other hand, unexplained first pass residual factor structure, as measured by the FACCHECK measure, is similar in magnitude when comparing the two-factor and five-factor across-stock time series regressions. These values do not differ significantly from zero, even at the 10% significance level, for the quality, and quality + ES, versions of the procedure. These factors, in combination with the market factor, thus capture the factor structure of the stock returns quite well, and the model with the SMB, HML, and MOM factors is not much more superior in capturing unexplained stock returns than just the quality factor and market factor combination. The *p*-values on the FACCHECK measure in the one-factor regression with quality-plus, quality, ES, and ES + quality factors indicate that these regressions leave significant unexplained factor structure in the first pass residuals. In the case of the quality-plus factor, there remains some unexplained factor structure in the residuals of the first pass two-factor regression, but one may observe from Panel C that the SMB, HML, and MOM factors capture this unexplained factor structure. In the case of the ES factor, unexplained residual factor structure remains, even after the addition of all factors. This also advocates that the SMB, HML, and MOM factors are not much more superior proxies for the unobserved factors in stock returns than just the ES factor.

In all, I find insignificantly negative risk premia on the quality-plus factor, as well as its constituents. These factors are not completely irrelevant as they are not shrunk to zero by the Pen-FM procedure. Therefore, although sorts indicate some advantages for going long in top quality-plus or ES stocks, such an effect does not hold across the board of levels in ES and quality-plus. One should note that the marginal effect of the quality factor that I find here is somewhat disappointing. This largely contributes the meagre marginal quality-plus effect, yet one should keep in mind that this is a sample period during which the quality effect is much less pronounced than the effect found in previous empirical evidence that considers other sample periods.

8. CONCLUSIONS

To conclude, there exists some evidence for a premium on employee satisfaction. In line with the research of Edmans (2011), I find that stocks on the lists of '100 Best Companies to Work for' attain abnormal excess returns. This finding is confirmed to hold for other geographic regions than the US (although not all) and the list premium persists over a longer sample period than the one that Edmans (2011) considers. Furthermore, when measuring employee satisfaction on a continuous scale, I find that high levels of employee satisfaction lead to superior excess stock returns. However, employee satisfaction and returns are not linearly related because a monotonically increasing pattern in ES decile portfolio returns is not observed, but I do find a difference in stock returns between the two extreme-end portfolios and such an effect is even more pronounced when sector effects are controlled for. Generally, high returns on a top-minus-bottom ES portfolio are mostly attributable to the outperformance of the highest ES decile stocks, as compared to the universe portfolio. However, some underperformance of the lowest ES decile stocks relative to universe is also observed. Abnormal factor-adjusted returns on stocks with high employee satisfaction are even more prevalent in European stocks and this holds for both indicators of high employee satisfaction: inclusion in the lists of '100 Best Companies to Work for' and a high score on the employee satisfaction criteria of RobecoSAM's Corporate Sustainability Assessment. Moreover, although the portfolios of the stocks of '100 Best Companies to Work for' lists have some exposure to the quality factor, further investigation shows that the premium on top employee satisfaction stocks is not attributable to the quality factor. Therefore, the relation between employee satisfaction and stock returns distinguishes itself from the relation between quality and stock returns.

A separate employee satisfaction factor is then shown not to improve the existing five-factor model in terms of explanatory power for stock returns. However, the addition of employee satisfaction to the quality score results in a quality-plus factor that can better explain stock returns in the five-factor model than the original quality-factor. Furthermore, long-short portfolios formed on the basis of rank-portfolio sorts on such a quality-plus score slightly outperform long-short portfolios formed on the basis of sorts on the original quality score. Lastly, the marginal effects of this quality-plus factor and a separate employee satisfaction factor on stock returns are quite meagre, yet so is the marginal effect of the quality factor for this time period. Hence, this does not necessarily mean that the quality-plus factor is redundant as evidence exists for a strong quality factor in other sample periods.

In the end, there is an employee satisfaction premium in stock returns but this effect is mainly present within high employee satisfaction stocks. That is to say, when choosing between two medium level employee satisfaction stocks, where one has a higher level of employee satisfaction as compared to the other, the evidence so far does not suggest that a choice based on employee satisfaction will be exceptionally fruitful. I now would like to formulate an answer to the initial research question about the relation of the employee satisfaction premium to the quality factor: the high employee satisfaction premium cannot be explained by the quality factor, but employee satisfaction may be used as a tool to augment the quality-factor.

However, this research is not without its limitations. Firstly, the investigation of the stocks from the '100 Best Companies to Work for' lists resulted in portfolios consisting of very small amounts of stocks due to lists also including non-public companies and due to stock listings in different regions than the origin of the list. This makes the inferences made from such a sample not particularly generalizable, even though I do confirm the high employee satisfaction effect within a much larger sample. Also, it might be the case that the '100 Best Companies to Work for' lists exclude firms whose stocks are severely underperforming. To my knowledge, there is no research into the selection bias of the companies on these lists, yet further research might investigate whether the companies on these lists have common characteristics other than their high levels of employee satisfaction. Furthermore, in that first part of the investigation I use the quality-minus-junk factor rather than the quality factor, this makes comparison between the results of the two measures of employee satisfaction rather uneven.

Furthermore, I investigate employee satisfaction and link it to the quality factor in a sample period during which the quality factor does not perform as well as during other time periods. Data limitation on employee satisfaction scores did not allow for a more robust quality time period. As there is not a very clear consensus on what should be a measure for employee satisfaction, further research might find an alternative proxy for employee satisfaction for which data on a longer sample period is available. If the employee satisfaction effect prevails during such a period, it would be of interest to repeat my investigation regarding its relation to the quality factor and the performance of the quality-plus factor.

Additionally, I only look into a potential link between employee satisfaction and the quality factor. Further research could investigate whether this employee satisfaction effect is attributable to another effect. For example, this employee satisfaction premium might be a part of a larger social effect, or even an overall ESG effect, and possibly should not be seen as a separate effect. It might even be that such an ESG effect is interlinked with the quality premium, but that such a link is not as easily observed when employee satisfaction is considered as an isolated signal. On the other hand, ESG might provide an additional quality signal that could also be used to improve the quality factor.

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APPENDIX

A1. Descriptive Statistics '100 Best Companies to Work for' Sample

TABLE A1

Descriptive Statistics List Returns

This table shows yearly descriptive statistics of the monthly returns of the stocks on the '100 Best Companies to Work for' lists. Returns are considered in percentage terms and are a total returns measure that contains dividends. These statistics are calculated over the cross-section of stocks once a year at the end of March, the last month of the portfolio holding period. Panel A shows the statistics for the full sample of stocks of firms on the '100 Best Companies to Work for' lists. Panels B, C, and D consider the European, US, and Latin-American lists separately.

Panel A: Full Sample

Year	# obs	Mean (%)	Median (%)	Std. Dev. (%)	Min (%)	Max (%)	5^{th} Percentile (%)	95^{th} Percentile (%)
2005	95	-1.07	-1.30	6.69	-23.26	32.15	-10.32	9.32
2006	88	1.97	1.27	6.06	-17.65	21.05	-6.67	11.14
2007	100	2.07	1.25	12.78	-18.16	109.41	-9.09	12.08
2008	93	0.64	1.24	8.89	-33.78	25.00	-14.99	13.20
2009	87	11.70	9.80	13.89	-7.64	104.09	-3.18	31.89
2010	82	5.97	5.40	8.73	-26.76	30.14	-6.23	17.69
2011	98	-0.25	0.48	6.19	-16.10	18.07	-9.33	12.53
2012	97	4.74	3.09	18.84	-32.86	174.29	-11.12	15.09
2013	91	3.36	3.95	5.60	-17.29	20.85	-6.42	12.34
2014	84	-0.34	-0.47	7.53	-31.61	24.42	-11.23	10.08
2015	73	-1.53	-1.48	5.23	-15.11	13.05	-8.72	6.38
2016	75	7.58	7.25	7.96	-9.03	40.78	-6.14	21.39

Panel B: Europe

Year	# obs	Mean (%)	Median (%)	Std. Dev. (%)	Min (%)	Max (%)	5^{th} Percentile (%)	95^{th} Percentile (%)
2004	21	-1.08	-1.31	6.54	-11.90	14.93	-9.52	9.53
2005	26	-1.45	-1.13	4.65	-11.30	9.32	-10.32	4.97
2006	25	2.76	3.87	7.26	-17.65	21.05	-5.61	12.41
2007	38	3.26	1.21	18.42	-13.72	109.41	-9.27	12.14
2008	31	-0.02	3.14	10.57	-33.78	13.74	-24.85	13.20
2009	31	12.80	9.37	19.23	-5.82	104.09	-2.24	31.89
2010	28	4.02	5.08	9.55	-26.76	17.67	-26.41	14.45
2011	35	0.28	1.15	6.93	-16.10	18.07	-10.02	15.02
2012	27	0.61	2.33	8.58	-32.86	10.23	-15.38	8.33
2013	25	2.98	3.95	6.17	-17.29	12.75	-6.74	12.34
2014	25	-1.12	-0.54	5.71	-11.99	8.45	-11.41	7.00
2015	18	-2.40	-1.08	4.80	-11.28	5.41	-11.28	5.41
2016	20	5.49	5.25	5.34	-2.60	18.08	-2.60	12.71

Panel C: US								
Year	**# obs**	**Mean (%)**	**Median (%)**	**Std. Dev. (%)**	**Min (%)**	**Max (%)**	**5th Percentile (%)**	**95th Percentile (%)**
1999	**64**	4.04	1.89	12.66	-29.20	41.11	-11.55	19.92
2000	**60**	8.86	11.74	18.56	-47.24	62.97	-23.81	36.82
2001	**55**	-9.01	-7.25	13.16	-67.94	20.37	-32.91	9.61
2002	**51**	5.85	6.36	9.08	-22.98	29.59	-8.34	18.64
2003	**49**	1.55	1.95	8.01	-21.72	24.92	-12.33	12.15
2004	**55**	-1.33	-1.44	6.22	-21.12	13.95	-10.07	11.08
2005	**52**	-1.33	-0.78	6.58	-23.26	19.94	-12.62	8.80
2006	**50**	1.91	1.15	6.00	-13.47	14.85	-9.34	11.14
2007	**42**	-0.20	-0.57	6.90	-18.16	25.54	-8.63	8.13
2008	**41**	1.57	1.08	7.94	-14.99	25.00	-11.96	13.39
2009	**40**	12.44	13.06	11.05	-7.64	38.27	-4.95	31.92
2010	**40**	6.21	6.00	8.13	-10.74	25.85	-9.34	17.69
2011	**42**	-0.67	-0.23	5.78	-10.33	13.15	-9.25	12.04
2012	**42**	4.85	4.06	5.87	-7.50	20.31	-3.67	13.32
2013	**46**	4.28	4.25	5.38	-9.63	20.85	-4.82	12.34
2014	**42**	-1.32	-0.75	8.54	-31.61	24.42	-11.23	7.51
2015	**41**	-0.74	-0.96	5.67	-15.11	13.05	-8.72	8.31
2016	**38**	8.05	7.68	9.02	-9.03	40.78	-8.66	27.11

Panel D: Latin America								
Year	**# obs**	**Mean (%)**	**Median (%)**	**Std. Dev. (%)**	**Min (%)**	**Max (%)**	**5th Percentile (%)**	**95th Percentile (%)**
2005	**17**	0.29	-2.63	9.43	-6.98	32.15	-6.98	32.15
2006	**13**	0.70	0.45	3.25	-4.53	6.51	-4.53	6.51
2007	**20**	4.60	3.20	8.19	-5.88	34.99	-5.88	12.92
2008	**21**	-0.22	0.96	8.15	-29.11	8.78	-8.52	8.78
2009	**16**	7.71	7.14	5.31	-1.97	16.28	-2.00	16.28
2010	**14**	9.19	4.99	8.22	2.15	30.14	2.15	30.14
2011	**21**	-0.27	1.38	5.89	-10.21	12.04	-9.26	6.30
2012	**28**	8.56	2.09	33.26	-11.55	174.29	-11.12	21.12
2013	**20**	1.72	2.56	5.18	-6.74	10.37	-6.74	10.37
2014	**17**	3.24	2.44	6.40	-8.32	17.08	-8.32	17.08
2015	**14**	-2.72	-2.44	4.21	-8.32	3.08	-8.32	3.08
2016	**17**	9.00	6.84	7.93	-2.50	23.68	-2.50	23.68

TABLE A2

Descriptive Statistics List Market Capitalizations

This table shows yearly descriptive statistics of the market capitalizations of the stocks on the '100 Best Companies to Work for' lists. Market capitalizations are denoted in billions of dollars. These statistics are calculated over the cross-section of stocks once a year at the end of March. Panel A shows the statistics for the full sample of stocks of firms on the '100 Best Companies to Work for' lists. Panels B, C, and D consider the European, US, and Latin-American lists separately.

Panel A: Full Sample

Year	# obs	Mean (bln $)	Median (bln $)	Std. Dev. (bln $)	Min (bln $)	Max (bln $)	5th Percentile (bln $)	95th Percentile (bln $)
2004	93	59.15	22.45	75.63	0.10	307.60	0.75	267.26
2005	87	51.46	18.70	74.46	0.00	382.23	0.44	222.23
2006	99	59.47	34.46	75.65	0.05	362.53	0.50	281.17
2007	93	57.60	42.16	62.92	0.05	272.91	1.02	199.29
2008	86	54.70	30.24	70.67	0.00	369.43	0.93	215.64
2009	82	30.94	13.85	40.57	0.00	163.32	0.24	101.73
2010	98	47.80	23.48	61.29	0.00	256.87	0.13	179.71
2011	96	40.65	17.79	49.92	0.00	213.34	0.13	147.20
2012	91	46.95	17.74	62.61	0.00	270.64	0.09	165.42
2013	84	53.12	24.46	64.70	0.09	239.60	0.92	212.45
2014	73	55.50	22.02	79.87	0.05	340.25	0.37	313.01
2015	74	54.43	26.66	70.81	0.06	329.83	1.87	177.14

Panel B: Europe

Year	# obs	Mean (bln $)	Median (bln $)	Std. Dev. (bln $)	Min (bln $)	Max (bln $)	5th Percentile (bln $)	95th Percentile (bln $)
2003	21	68.99	40.94	71.57	0.17	259.08	1.25	191.94
2004	25	87.25	52.36	91.63	0.37	307.60	0.75	269.10
2005	25	81.95	49.75	96.82	0.00	382.23	1.44	262.77
2006	37	84.11	65.32	91.69	0.43	362.3	0.86	362.53
2007	31	76.42	60.91	64.55	0.05	272.91	0.57	199.29
2008	30	76.57	51.21	88.44	0.00	369.43	0.22	264.13
2009	28	38.91	19.90	43.32	0.00	163.32	0.01	101.73
2010	35	63.82	42.03	63.61	0.00	256.87	0.00	183.77
2011	27	46.57	35.69	48.02	0.00	213.34	0.00	103.09
2012	27	50.92	29.00	63.72	0.00	270.64	0.00	165.42
2013	24	59.11	38.15	63.06	0.10	239.60	4.04	180.23
2014	18	57.39	41.68	79.31	0.11	340.25	0.11	340.25
2015	19	72.35	50.53	83.16	1.87	329.83	1.87	329.83

Panel C: US								
Year	# obs	Mean (bln $)	Median (bln $)	Std. Dev. (bln $)	Min (bln $)	Max (bln $)	5th Percentile (bln $)	95th Percentile (bln $)
1998	64	36.02	10.35	52.81	0.07	217.92	0.31	130.43
1999	58	46.19	9.34	93.83	0.08	452.33	0.32	205.06
2000	54	78.92	11.83	140.87	0.11	553.02	0.26	537.80
2001	51	47.43	13.51	70.11	0.09	291.78	0.76	225.55
2002	49	45.37	13.37	72.44	0.14	326.64	0.99	203.84
2003	55	32.98	10.34	51.45	0.31	259.08	1.50	135.10
2004	51	45.72	15.00	64.46	0.66	269.10	1.24	176.18
2005	49	35.09	13.87	55.30	0.50	262.77	0.99	178.77
2006	42	42.00	15.29	57.66	0.50	281.17	1.40	133.28
2007	42	43.07	19.47	57.39	0.2	272.91	1.35	154.20
2008	40	33.95	19.84	48.50	0.93	264.13	1.27	104.91
2009	40	19.32	8.86	32.06	0.12	163.32	0.31	83.82
2010	41	33.64	11.30	51.52	0.14	256.87	0.78	138.93
2011	42	31.71	12.27	44.88	0.12	213.34	1.31	108.67
2012	45	35.61	15.35	53.10	0.09	270.64	1.35	140.46
2013	42	39.04	15.59	54.45	0.09	239.60	1.06	121.13
2014	41	49.88	18.86	75.71	0.17	340.25	2.34	154.48
2015	38	37.26	20.50	44.443	0.34	172.80	2.13	159.17

Panel D: Latin America								
Year	# obs	Mean (bln $)	Median (bln $)	Std. Dev. (bln $)	Min (bln $)	Max (bln $)	5th Percentile (bln $)	95th Percentile (bln $)
2004	17	58.11	24.29	74.11	0.10	269.10	0.10	269.10
2005	13	54.53	28.38	75.53	0.04	262.77	0.04	262.77
2006	20	50.57	37.06	66.88	0.05	281.17	0.05	133.28
2007	20	58.92	49.25	66.61	0.14	272.91	0.14	158.37
2008	16	65.55	51.38	69.54	0.13	264.13	0.13	264.13
2009	14	48.16	31.23	49.00	0.10	163.32	0.10	163.32
2010	22	48.67	11.68	70.17	0.07	256.87	0.07	149.04
2011	27	48.66	17.83	58.22	0.13	213.34	0.31	152.26
2012	19	68.17	42.70	77.60	0.00	270.64	0.00	270.64
2013	18	78.00	52.15	81.91	0.33	239.60	0.33	239.60
2014	14	69.54	38.12	95.65	0.05	340.25	0.05	340.25
2015	17	72.79	53.58	95.35	0.06	329.83	0.06	329.83

TABLE A3

Descriptive Statistics List Book-to-Price Ratios

This table shows yearly descriptive statistics of the book-to-price ratios of the stocks on the '100 Best Companies to Work for' lists. These statistics are calculated over the cross-section of stocks once a year at the end of March. Panel A shows the statistics for the full sample of stocks of firms on the '100 Best Companies to Work for' lists. Panels B, C, and D consider the European, US, and Latin-American lists separately.

Panel A: Full Sample

Year	# obs	Mean	Median	Std. Dev.	Min	Max	5th Percentile	95th Percentile
2004	**93**	0.30	0.25	0.19	0.03	1.18	0.10	0.68
2005	**85**	0.31	0.27	0.18	0.08	0.92	0.11	0.66
2006	**97**	0.29	0.25	0.17	0.05	0.86	0.09	0.75
2007	**89**	0.29	0.22	0.21	0.07	1.46	0.10	0.74
2008	**85**	0.43	0.24	0.84	0.09	7.55	0.12	0.87
2009	**80**	0.60	0.35	0.67	0.09	4.78	0.12	1.65
2010	**96**	0.44	0.29	0.53	0.05	4.72	0.09	1.10
2011	**96**	0.44	0.30	0.35	0.07	2.00	0.08	1.15
2012	**86**	0.43	0.28	0.49	0.04	3.89	0.08	1.16
2013	**82**	0.38	0.29	0.31	0.04	1.27	0.08	1.15
2014	**69**	0.38	0.28	0.30	0.05	1.58	0.07	0.94
2015	**72**	0.32	0.24	0.26	0.05	1.06	0.06	0.97

Panel B: Europe

Year	# obs	Mean	Median	Std. Dev.	Min	Max	5th Percentile	95th Percentile
2003	**21**	0.26	0.22	0.16	0.09	0.61	0.10	0.56
2004	**24**	0.31	0.26	0.24	0.03	1.18	0.08	0.59
2005	**23**	0.29	0.24	0.19	0.08	0.92	0.09	0.57
2006	**35**	0.26	0.21	0.14	0.05	0.52	0.08	0.49
2007	**28**	0.24	0.18	0.12	0.07	0.51	0.08	0.45
2008	**29**	0.62	0.24	1.39	0.09	7.55	0.11	2.17
2009	**26**	0.71	0.36	0.96	0.10	4.78	0.12	1.82
2010	**31**	0.56	0.32	0.85	0.05	4.72	0.09	1.75
2011	**24**	0.47	0.31	0.49	0.08	2.00	0.08	1.65
2012	**22**	0.51	0.29	0.79	0.09	3.89	0.12	1.16
2013	**22**	0.31	0.27	0.25	0.08	1.27	0.12	0.47
2014	**15**	0.42	0.33	0.39	0.06	1.58	0.06	1.58
2015	**19**	0.32	0.27	0.25	0.05	1.03	0.05	1.03

Panel C: US								
Year	**# obs**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**5th Percentile**	**95th Percentile**
1998	**64**	0.27	0.23	0.20	0.03	1.02	0.05	0.59
1999	**58**	0.30	0.23	0.28	0.04	1.73	0.05	0.79
2000	**53**	0.26	0.16	0.29	0.01	1.56	0.02	0.77
2001	**51**	0.37	0.21	0.78	0.01	5.61	0.06	0.71
2002	**48**	0.27	0.20	0.26	0.02	1.45	0.06	0.54
2003	**54**	0.34	0.25	0.23	0.01	1.09	0.09	0.75
2004	**51**	0.29	0.24	0.17	0.05	0.77	0.11	0.69
2005	**49**	0.32	0.27	0.18	0.09	0.85	0.11	0.66
2006	**42**	0.32	0.26	0.20	0.08	0.86	0.11	0.76
2007	**42**	0.32	0.23	0.25	0.08	1.46	0.12	0.74
2008	**40**	0.33	0.27	0.22	0.10	1.33	0.11	0.66
2009	**41**	0.60	0.39	0.49	0.09	2.36	0.12	1.52
2010	**42**	0.36	0.27	0.27	0.06	1.18	0.09	0.72
2011	**44**	0.36	0.26	0.29	0.07	1.33	0.08	0.95
2012	**45**	0.39	0.27	0.34	0.04	1.41	0.08	1.10
2013	**41**	0.41	0.31	0.33	0.04	1.27	0.08	1.15
2014	**41**	0.35	0.28	0.25	0.05	0.94	0.07	0.90
2015	**38**	0.30	0.22	0.26	0.05	1.03	0.05	0.93

Panel D: Latin America								
Year	**# obs**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**5th Percentile**	**95th Percentile**
2004	**18**	0.33	0.30	0.20	0.11	0.68	0.11	0.68
2005	**13**	0.31	0.31	0.18	0.16	0.85	0.16	0.85
2006	**20**	0.26	0.25	0.14	0.14	0.75	0.14	0.50
2007	**19**	0.29	0.22	0.23	0.07	0.89	0.07	0.89
2008	**16**	0.33	0.16	0.32	0.12	1.25	0.12	1.25
2009	**13**	0.39	0.22	0.36	0.15	1.30	0.15	1.30
2010	**23**	0.43	0.47	0.24	0.10	1.04	0.17	0.74
2011	**28**	0.52	0.51	0.29	0.12	0.97	0.16	0.90
2012	**19**	0.45	0.28	0.36	0.13	1.28	0.13	1.28
2013	**19**	0.37	0.22	0.31	0.13	1.22	0.13	1.22
2014	**13**	0.41	0.22	0.33	0.15	1.15	0.15	1.15
2015	**15**	0.37	0.28	0.30	0.10	1.06	0.10	1.06

A2. Descriptive Statistics Corporate Sustainability Assessment (CSA) Sample

TABLE A4

Descriptive Statistics CSA Sample Returns

This table shows yearly descriptive statistics of the monthly returns of the stocks with observations on all three of the employee satisfaction criteria of the CSA. Returns are considered in percentage terms and are a total returns measure that contains dividends. These statistics are calculated over the cross-section of stocks once a year at the end of October, the first month of the portfolio holding period. Panel A shows the statistics for the entire CSA sample, while Panels B and C show the descriptive statistics for the European CSA sample and North American CSA sample, respectively.

Panel A: Full Sample

Year	# obs	Mean (%)	Median (%)	Std. Dev. (%)	Min (%)	Max (%)	5th Percentile (%)	95th Percentile (%)
2003	**418**	6.70	6.66	6.53	-21.73	35.96	-3.27	16.69
2004	**589**	4.01	3.74	5.68	-27.01	28.37	-4.57	13.30
2005	**565**	3.54	2.87	6.44	-31.26	40.35	-5.42	14.56
2006	**592**	2.64	2.58	5.59	-15.53	26.04	-6.15	11.34
2007	**607**	-1.33	-1.40	6.67	-23.16	38.21	-12.26	9.13
2008	**777**	7.94	6.48	13.41	-43.15	84.02	-12.53	31.23
2009	**1216**	4.15	3.64	7.91	-25.73	91.71	-6.85	17.03
2010	**1236**	8.19	7.50	7.05	-16.32	41.14	-1.94	20.44
2011	**1418**	-1.49	-1.11	7.29	-46.17	41.52	-14.26	8.58
2012	**1591**	4.04	3.14	7.19	-32.84	68.02	-5.35	16.40
2013	**1794**	1.47	1.42	6.39	-35.42	44.71	-8.29	10.89
2014	**1539**	-2.38	-1.98	7.76	-44.42	67.38	-14.99	8.00
2015	**2123**	-1.59	-1.08	8.94	-94.22	71.72	-14.81	10.82

Panel B: Europe

Year	# obs	Mean (%)	Median (%)	Std. Dev. (%)	Min (%)	Max (%)	5th Percentile (%)	95th Percentile (%)
2003	**198**	6.55	6.57	5.45	-13.89	22.71	-2.38	15.63
2004	**248**	4.24	4.17	5.99	-27.01	23.89	-4.16	14.71
2005	**213**	4.61	4.28	4.89	-7.84	20.07	-3.14	12.58
2006	**219**	4.30	4.01	5.15	-7.45	25.51	-3.14	13.28
2007	**226**	-1.87	-2.45	6.69	-22.38	38.21	-12.26	7.67
2008	**279**	8.74	7.46	12.24	-43.15	48.94	-11.80	29.87
2009	**350**	2.46	2.74	6.14	-17.89	30.98	-5.89	12.43
2010	**363**	10.06	9.66	7.23	-11.54	35.82	-0.09	22.12
2011	**366**	-3.12	-2.88	5.98	-25.65	25.46	-13.64	5.24
2012	**416**	4.28	3.81	5.73	-20.93	24.20	-3.63	15.13
2013	**421**	2.66	2.97	5.35	-21.10	44.71	-4.75	9.99
2014	**374**	-2.93	-2.54	6.10	-44.42	15.16	-13.02	6.93
2015	**502**	-1.57	-0.84	8.19	-94.22	30.18	-12.45	8.99

Panel C: North America								
Year	# obs	Mean (%)	Median (%)	Std. Dev. (%)	Min (%)	Max (%)	5th Percentile (%)	95th Percentile (%)
2003	110	5.33	5.69	6.82	-17.08	21.21	-7.08	15.86
2004	185	3.82	3.68	5.62	-11.40	28.37	-4.96	12.20
2005	203	0.61	0.38	5.43	-31.26	16.88	-6.65	9.51
2006	203	0.11	0.69	5.24	-15.53	24.57	-8.09	7.54
2007	177	-0.41	-0.67	6.84	-23.16	26.56	-12.48	9.20
2008	215	3.85	2.99	12.13	-29.35	51.27	-15.66	24.36
2009	375	4.52	3.86	7.58	-13.72	47.01	-6.09	15.01
2010	356	6.53	5.80	6.00	-13.95	25.86	-3.10	17.24
2011	425	-1.00	-0.18	7.07	-46.17	21.30	-14.46	7.82
2012	485	2.23	1.57	5.60	-15.29	34.16	-5.73	11.91
2013	516	2.58	2.31	5.55	-24.36	35.36	-5.32	10.69
2014	366	0.32	0.20	7.18	-29.45	67.38	-9.19	9.24
2015	427	-3.60	-2.93	8.74	-45.41	71.72	-16.54	6.66

TABLE A5

Descriptive Statistics CSA Sample Market Capitalizations

This table shows yearly descriptive statistics of the market capitalizations of the stocks with observations on all three of the employee satisfaction criteria of the CSA. Market capitalizations are denoted in billions of dollars. These statistics are calculated over the cross-section of stocks once a year at the end of September. Panel A shows the statistics for the entire CSA sample, while Panels B and C show the descriptive statistics for the European CSA sample and North American CSA sample, respectively.

Panel A: Full Sample								
Year	# obs	Mean (bln $)	Median (bln $)	Std. Dev. (bln $)	Min (bln $)	Max (bln $)	5th Percentile (bln $)	95th Percentile (bln $)
2003	414	16.35	5.36	35.42	0.14	287.27	0.66	74.39
2004	586	15.58	5.02	34.48	0.17	373.40	0.86	65.50
2005	564	18.38	7.47	34.25	0.16	378.63	1.31	74.67
2006	592	21.53	8.49	40.03	0.25	464.73	1.68	85.29
2007	603	23.57	8.89	44.17	0.33	494.48	1.45	108.18
2008	775	12.08	4.07	26.97	0.02	416.30	0.45	48.74
2009	1205	12.34	4.38	25.71	0.11	360.77	0.71	49.39
2010	1230	13.00	5.40	24.84	0.10	354.19	0.72	51.18
2011	1405	12.69	4.97	25.68	0.12	391.11	0.74	50.47
2012	1572	12.37	4.86	26.13	0.11	406.85	0.81	44.94
2013	1768	13.50	4.92	28.64	0.08	411.46	0.63	52.71
2014	1524	15.11	5.27	31.63	0.04	393.95	0.70	61.98
2015	2060	11.03	3.36	26.17	0.06	434.69	0.37	44.23

Panel B: Europe								
Year	**# obs**	**Mean (bln $)**	**Median (bln $)**	**Std. Dev. (bln $)**	**Min (bln $)**	**Max (bln $)**	**5th Percentile (bln $)**	**95th Percentile (bln $)**
2003	**195**	12.85	4.57	24.17	0.26	156.56	0.82	61.05
2004	**246**	13.53	5.10	26.39	0.49	222.22	0.99	64.97
2005	**213**	17.05	7.33	30.16	0.33	230.73	1.31	74.67
2006	**219**	21.40	9.54	32.98	1.27	223.01	2.16	88.94
2007	**224**	25.54	9.62	40.05	1.34	231.25	2.19	134.10
2008	**278**	11.76	4.10	22.29	0.18	151.59	0.51	54.46
2009	**348**	13.53	5.02	24.54	0.38	176.75	1.21	56.24
2010	**363**	12.62	5.29	22.59	0.20	189.64	0.93	56.31
2011	**366**	13.11	5.14	23.79	0.25	194.73	1.05	53.65
2012	**415**	12.72	5.03	24.01	0.22	211.12	0.75	59.36
2013	**419**	15.61	5.95	29.01	0.21	236.24	0.87	66.78
2014	**373**	17.01	6.99	30.26	0.43	262.61	1.18	70.02
2015	**498**	12.60	4.85	24.97	0.09	236.82	0.51	54.64

Panel C: North America								
Year	**# obs**	**Mean (bln $)**	**Median (bln $)**	**Std. Dev. (bln $)**	**Min (bln $)**	**Max (bln $)**	**5th Percentile (bln $)**	**95th Percentile (bln $)**
2003	**109**	32.66	10.80	57.03	0.31	287.27	0.91	159.33
2004	**184**	25.37	7.50	50.96	0.46	373.40	1.30	117.97
2005	**202**	26.38	10.63	45.19	0.98	378.63	1.84	112.09
2006	**203**	30.71	12.12	55.38	0.74	464.73	2.10	113.36
2007	**177**	34.43	13.80	62.77	0.86	494.48	2.07	163.13
2008	**215**	20.32	6.73	41.82	0.17	416.30	0.71	93.17
2009	**374**	19.42	6.82	36.08	0.73	360.77	1.70	86.24
2010	**355**	21.44	9.38	35.77	0.72	354.19	2.11	95.09
2011	**422**	21.48	9.14	37.40	0.63	391.11	1.85	97.92
2012	**482**	20.19	8.12	37.76	0.17	406.85	1.52	87.77
2013	**512**	23.45	9.87	41.16	0.46	411.46	1.65	93.18
2014	**364**	31.66	13.82	49.71	1.40	393.95	3.21	125.57
2015	**423**	26.26	10.88	44.33	0.86	434.69	1.77	104.86

TABLE A6

Descriptive Statistics CSA Sample Book-to-Price Ratios

This table shows yearly descriptive statistics of the book-to-price ratios of stocks with observations on all three of the employee satisfaction criteria of the CSA. These statistics are calculated over the cross-section of stocks once a year at the end of September. Panel A shows the statistics for the entire CSA sample, while Panels B and C show the descriptive statistics for the European CSA sample and North American CSA sample, respectively.

Panel A: Full Sample

Year	# obs	Mean	Median	Std. Dev.	Min	Max	5th Percentile	95th Percentile
2003	416	0.51	0.44	0.31	0.09	1.50	0.11	1.03
2004	588	0.45	0.40	0.25	0.09	1.22	0.11	0.93
2005	565	0.40	0.36	0.22	0.08	1.04	0.11	0.86
2006	592	0.40	0.36	0.22	0.07	0.99	0.10	0.84
2007	607	0.41	0.36	0.25	0.06	1.03	0.10	0.97
2008	776	0.86	0.67	0.65	0.14	2.76	0.15	2.48
2009	1216	0.60	0.51	0.38	0.09	1.54	0.11	1.48
2010	1236	0.57	0.50	0.36	0.08	1.39	0.11	1.39
2011	1418	0.67	0.55	0.46	0.10	1.86	0.12	1.79
2012	1591	0.65	0.53	0.46	0.09	1.97	0.10	1.65
2013	1794	0.55	0.45	0.38	0.07	1.59	0.09	1.41
2014	1538	0.55	0.44	0.41	0.07	1.72	0.08	1.45
2015	2120	0.61	0.45	0.52	0.07	2.25	0.09	1.80

Panel B: Europe

Year	# obs	Mean	Median	Std. Dev.	Min	Max	5th Percentile	95th Percentile
2003	197	0.55	0.49	0.33	0.09	1.50	0.09	1.12
2004	247	0.45	0.38	0.28	0.09	1.22	0.09	1.05
2005	213	0.41	0.35	0.25	0.08	1.04	0.08	0.87
2006	219	0.36	0.32	0.21	0.07	0.99	0.10	0.81
2007	226	0.38	0.32	0.24	0.06	1.03	0.11	0.94
2008	278	0.81	0.60	0.65	0.14	2.76	0.14	2.46
2009	350	0.53	0.44	0.35	0.09	1.54	0.10	1.23
2010	363	0.51	0.42	0.35	0.08	1.39	0.10	1.27
2011	366	0.64	0.51	0.46	0.10	1.86	0.11	1.81
2012	416	0.62	0.48	0.47	0.09	1.97	0.09	1.72
2013	421	0.50	0.42	0.36	0.07	1.59	0.09	1.26
2014	373	0.47	0.37	0.35	0.07	1.72	0.07	1.17
2015	501	0.49	0.35	0.44	0.07	2.25	0.08	1.37

Panel C: North America								
Year	# obs	Mean	Median	Std. Dev.	Min	Max	5th Percentile	95th Percentile
2003	110	0.34	0.29	0.20	0.04	0.96	0.11	0.78
2004	186	0.37	0.33	0.18	0.03	0.99	0.12	0.72
2005	203	0.34	0.31	0.20	-0.06	1.57	0.10	0.71
2006	203	0.37	0.34	0.21	-0.02	1.54	0.10	0.72
2007	177	0.35	0.30	0.24	0.00	1.71	0.10	0.82
2008	215	0.84	0.57	0.98	0.01	7.16	0.13	2.60
2009	375	0.46	0.41	0.28	-0.05	1.84	0.07	0.98
2010	356	0.44	0.40	0.27	-0.05	1.63	0.09	0.94
2011	425	0.50	0.42	0.38	-0.02	3.88	0.10	1.08
2012	485	0.47	0.41	0.32	-0.06	3.08	0.08	1.04
2013	516	0.41	0.34	0.33	-0.08	3.68	0.07	0.89
2014	366	0.41	0.32	0.38	-0.10	3.79	0.07	1.08
2015	427	0.49	0.35	0.63	-0.27	6.80	0.05	1.50

TABLE A7

Descriptive Statistics CSA Sample Quality Scores

This table shows yearly descriptive statistics of the quality scores of stocks with observations on all three of the employee satisfaction criteria of the CSA. These statistics are calculated over the cross-section of stocks once a year at the end of September. Quality scores are constructed, in the manner of Kyosev (2013), as the average of the z-scores of gross profits to assets, negative accruals, and free cash flows to assets. Panel A shows the statistics for the entire CSA sample, while Panels B and C show the descriptive statistics for the European CSA sample and North American CSA sample, respectively.

Panel A: Full Sample								
Year	# obs	Mean	Median	Std. Dev.	Min	Max	5th Percentile	95th Percentile
2003	408	0.07	0.01	0.58	-1.97	2.48	-0.76	0.97
2004	579	0.16	0.11	0.59	-1.49	3.06	-0.66	1.20
2005	559	0.14	0.06	0.56	-1.62	2.04	-0.64	1.12
2006	582	0.09	0.03	0.56	-1.84	1.97	-0.66	1.07
2007	598	0.11	0.07	0.58	-2.01	2.60	-0.73	1.09
2008	768	0.06	0.00	0.61	-2.21	3.07	-0.82	1.14
2009	1203	0.03	-0.03	0.58	-2.24	2.76	-0.77	1.08
2010	1220	0.05	0.02	0.63	-2.16	2.99	-0.96	1.17
2011	1391	0.03	-0.02	0.61	-2.12	2.34	-0.88	1.13
2012	1555	0.02	-0.05	0.61	-2.07	2.86	-0.88	1.17
2013	1738	0.00	-0.07	0.61	-2.22	2.70	-0.86	1.14
2014	1477	0.04	-0.03	0.61	-2.24	3.46	-0.81	1.15
2015	2030	0.00	-0.07	0.61	-2.41	2.68	-0.84	1.18

Panel B: Europe								
Year	**# obs**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**5th Percentile**	**95th Percentile**
2003	**195**	0.02	-0.05	0.58	-1.66	2.49	-0.78	1.04
2004	**243**	0.11	0.05	0.63	-1.52	3.09	-0.76	1.18
2005	**209**	0.04	-0.06	0.67	-1.66	2.11	-0.92	1.23
2006	**213**	0.00	-0.03	0.62	-2.04	2.09	-1.21	1.00
2007	**224**	0.03	0.04	0.56	-2.31	1.92	-0.86	0.98
2008	**275**	-0.01	-0.04	0.62	-1.92	2.18	-0.89	1.12
2009	**346**	0.00	-0.07	0.69	-1.98	3.33	-0.89	1.14
2010	**358**	0.01	-0.04	0.71	-1.96	3.15	-1.19	1.33
2011	**361**	0.03	-0.05	0.64	-2.08	2.51	-0.88	1.26
2012	**411**	-0.03	-0.13	0.65	-2.37	2.69	-0.82	1.23
2013	**412**	-0.03	-0.10	0.58	-2.02	2.47	-0.77	1.08
2014	**362**	0.04	-0.08	0.62	-1.69	3.42	-0.75	1.22
2015	**484**	0.01	-0.05	0.63	-2.46	2.73	-0.79	1.30

Panel C: North America								
Year	**# obs**	**Mean**	**Median**	**Std. Dev.**	**Min**	**Max**	**5th Percentile**	**95th Percentile**
2003	**110**	0.04	-0.03	0.60	-1.83	1.93	-0.81	1.19
2004	**185**	0.11	0.06	0.57	-1.20	1.84	-0.74	1.11
2005	**203**	0.18	0.19	0.56	-1.28	1.69	-0.66	1.05
2006	**204**	0.11	0.03	0.58	-1.38	1.80	-0.66	1.09
2007	**178**	0.12	0.09	0.58	-1.55	2.23	-0.71	1.19
2008	**216**	0.03	-0.09	0.64	-1.80	2.88	-0.86	1.16
2009	**376**	0.01	-0.02	0.55	-1.94	1.78	-0.77	1.06
2010	**357**	0.03	-0.04	0.63	-1.97	2.18	-0.86	1.15
2011	**426**	0.03	-0.07	0.61	-1.93	2.22	-0.83	1.09
2012	**485**	0.02	-0.03	0.59	-1.90	2.04	-0.80	1.07
2013	**516**	0.02	-0.04	0.59	-1.80	2.20	-0.83	1.09
2014	**366**	0.01	-0.04	0.60	-1.61	1.83	-0.89	1.16
2015	**434**	-0.02	-0.04	0.60	-1.73	2.02	-0.90	1.06

A3. Results '100 Best Companies to Work for' Sample

FIGURE A1

Average Monthly Performance of Full Sample Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the Full Sample portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 2004 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May})\ldots(1+\bar{r}_{March})$.

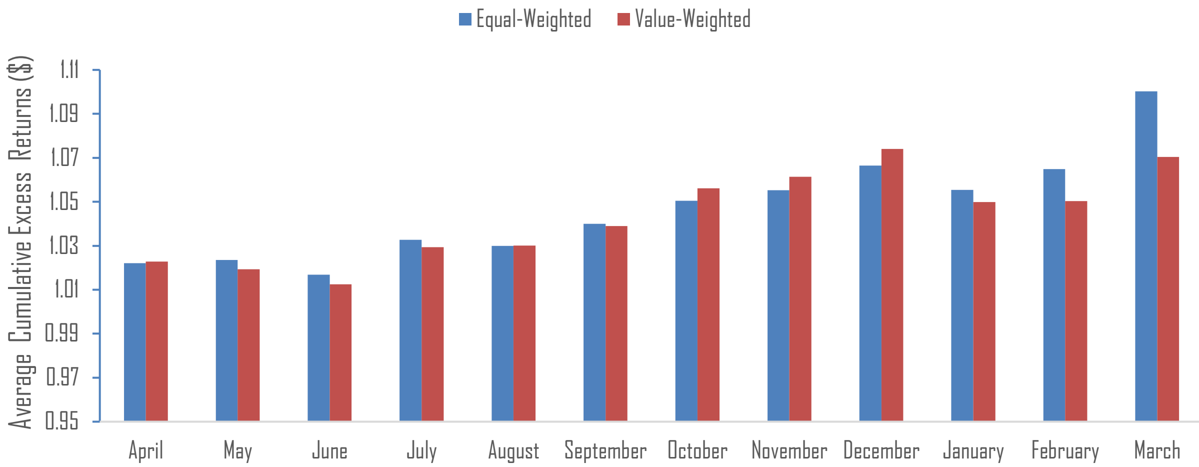

FIGURE A2

Average Monthly Performance of Europe Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the Europe portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 2003 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May})\ldots(1+\bar{r}_{March})$.

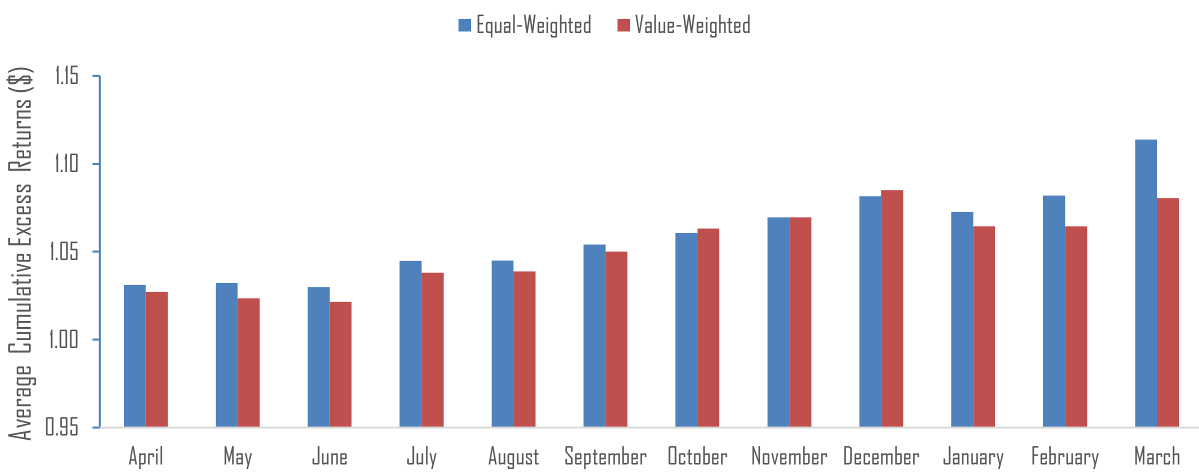

FIGURE A3

Average Monthly Performance of Europe-Home Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the Europe-Home portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 2003 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May})\,.\;\;.\;\;.(1+\;\bar{r}_{March})$.

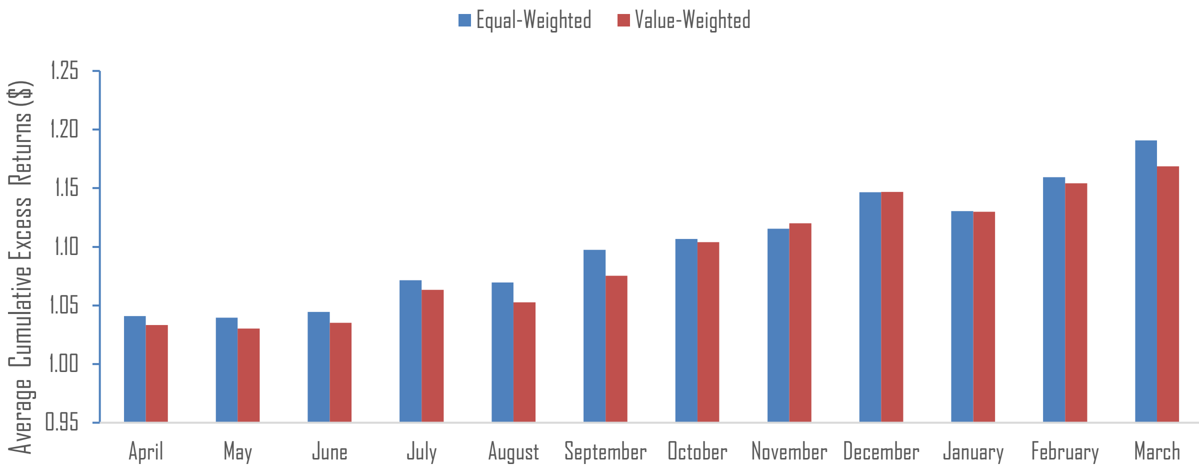

FIGURE A4

Average Monthly Performance of Europe-Foreign Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the Europe-Foreign portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 2003 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May})\,.\;\;.\;\;.(1+\;\bar{r}_{March})$.

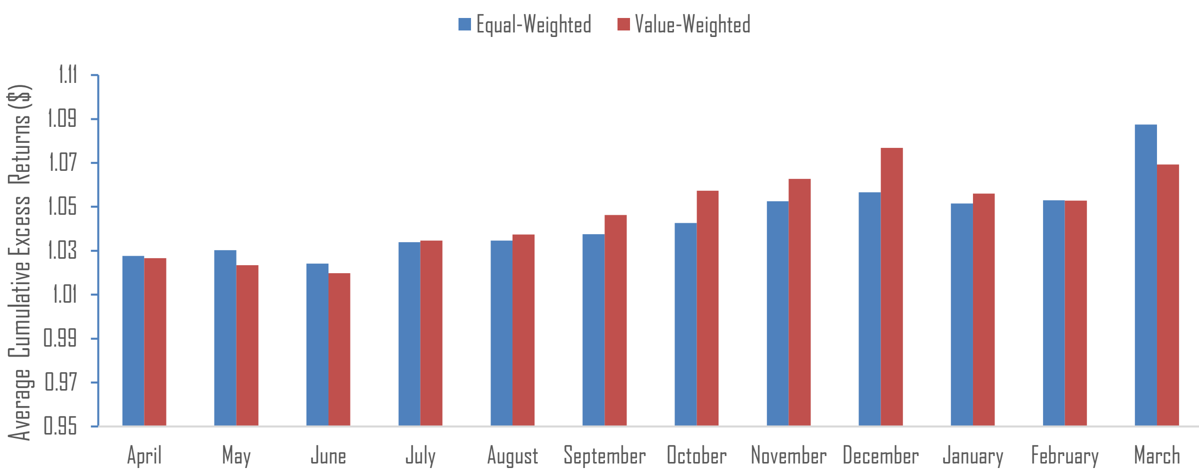

FIGURE A5

Average Monthly Performance of US Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the US portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 1998 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May})\ .\ \ .\ \ .(1+\ \bar{r}_{March})$.

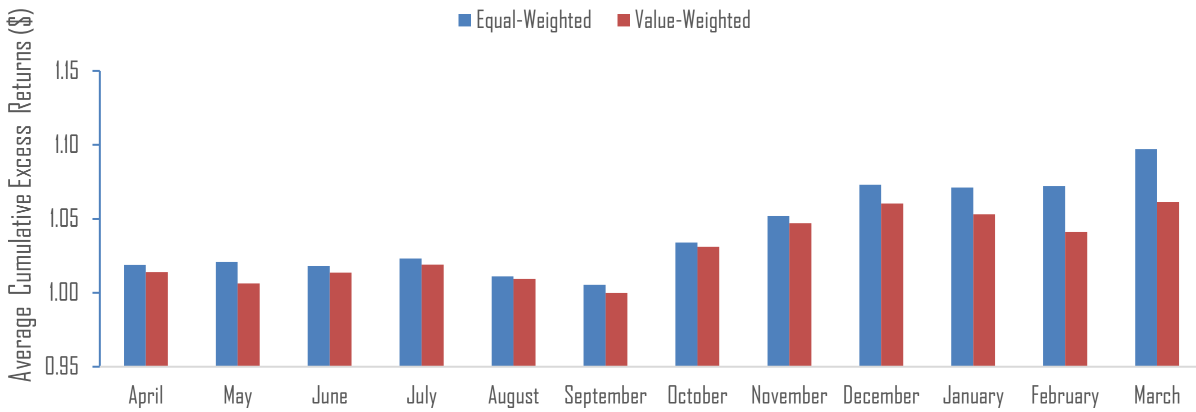

FIGURE A6

Average Monthly Performance of Latin America Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the Latin America portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 2004 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May})\ .\ \ .\ \ .(1+\ \bar{r}_{March})$.

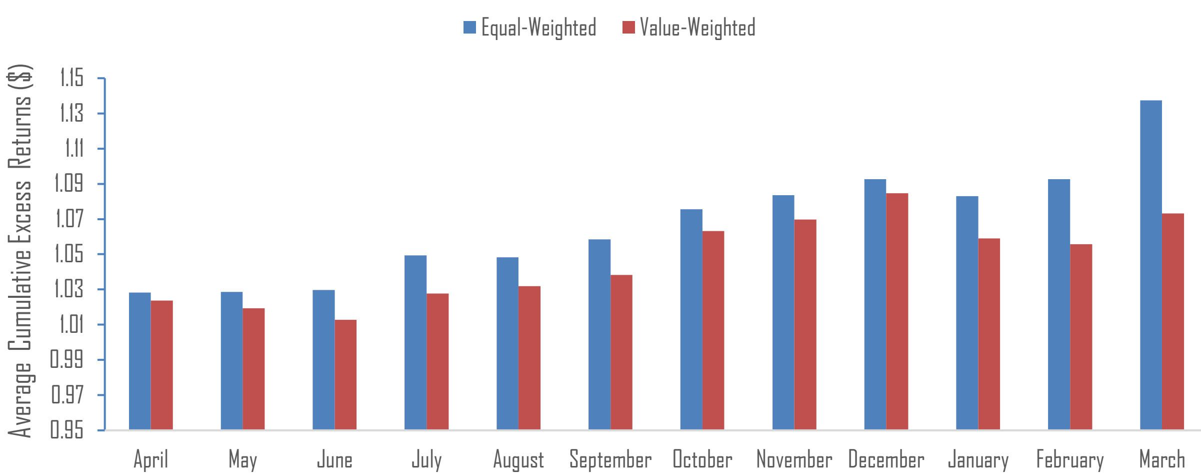

FIGURE A7

Average Monthly Performance of Latin-Foreign Portfolios

This figure shows the average cumulative compound excess returns of 1 dollar being invested in the Latin-Foreign portfolios at the end of March and then held up to and including the month indicated on the horizontal axis. Monthly excess returns on the portfolios are first calculated for the sample period of April 2004 – March 2016. Then month average excess returns are calculated and cumulative compound excess are calculated as $(1+\bar{r}_{April})(1+\bar{r}_{May}).\;.\;.(1+\;\bar{r}_{March})$.

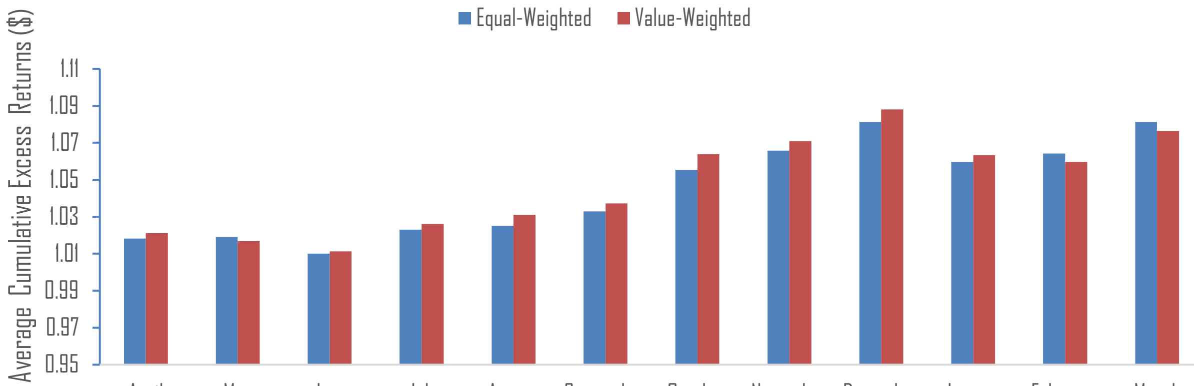

TABLE A8

Factor-Adjusted Returns of Equal-Weighted New Arrivals Portfolios

This table shows the key performance measures and the regression results of equal-weighted portfolios formed out of the stocks of those firms that are new on the '100 Best Companies to Work for' lists i.e. firms that appeared on the most recent yearly list but were not on the list the year before that. For these portfolios the sample period starts 1 year later than indicated in Table 2. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panel B shows the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression. In these regressions monthly excess returns of these equal-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. Panel B also reports the adjusted R-squared values of the regressions.

			Panel A: Performance Measures				
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	7.47	13.82	27.30	5.06	6.33	5.54	7.24
Volatility	17.76	26.34	22.07	19.51	22.12	14.83	17.00
Sharpe	0.42	0.52	1.24	0.26	0.29	0.37	0.43
			Panel B: Factor Regressions				
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
1-F α	0.12	0.58	1.55***	-0.29	0.08	0.21	0.31
	(0.54)	(1.10)	(5.38)	(-1.44)	(0.30)	(0.56)	(0.95)
Adj. R^2	0.76	0.31	0.59	0.79	0.63	0.26	0.26
4-F α	0.17	0.64*	1.40***	-0.22	-0.06	0.13	0.20
	(0.77)	(1.67)	(5.29)	(-1.09)	(-0.22)	(0.34)	(0.54)
Adj. R^2	0.76	0.30	0.59	0.81	0.67	0.27	0.30
5-F α	-0.18	0.13	1.29***	-0.01	-0.21	-0.07	-0.08
	(-0.71)	(0.37)	(3.31)	(-0.05)	(-0.74)	(-0.12)	(-0.18)
Adj. R^2	0.77	0.30	0.59	0.82	0.67	0.27	0.30

TABLE A9

Factor-Adjusted Returns of Value-Weighted New Arrivals Portfolios

This table shows the key performance measures and the regression results of value-weighted portfolios formed out of the stocks of those firms that are new on the '100 Best Companies to Work for' lists i.e. firms that appeared on the most recent yearly list but were not on the list the year before that. For these portfolios the sample period starts 1 year later than indicated in Table 2. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panel B shows the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression. In these regressions monthly excess returns of these value-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. Panel B also reports the adjusted R-squared values of the regressions.

	Panel A: Performance Measures						
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	4.46	5.37	25.89	3.72	3.52	6.27	7.24
Volatility	16.29	15.81	20.92	18.42	20.75	15.53	17.00
Sharpe	0.27	0.34	1.24	0.20	0.17	0.40	0.43
	Panel B: Factor Regressions						
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
1-F α	-0.09	0.00	1.63***	-0.35	-0.09	0.24	0.31
	(-0.50)	(0.01)	(4.78)	(-1.63)	(-0.32)	(0.65)	(0.95)
Adj. R^2	0.79	0.66	0.26	0.77	0.56	0.31	0.26
4-F α	-0.11	0.00	1.21***	-0.35*	-0.10	0.14	0.20
	(-0.68)	(-0.01)	(2.74)	(-1.83)	(-0.36)	(0.39)	(0.54)
Adj. R^2	0.80	0.66	0.31	0.82	0.60	0.35	0.30
5-F α	-0.57***	-0.70***	1.70***	-0.39*	-0.35	0.06	-0.08
	(-2.68)	(-2.70)	(3.25)	(-1.91)	(-1.59)	(0.12)	(-0.18)
Adj. R^2	0.83	0.70	0.32	0.81	0.61	0.35	0.30

TABLE A10

Factor-Adjusted Returns of Equal-Weighted Delisted Portfolios

This table shows the key performance measures and the regression results of equal-weighted portfolios formed out of the stocks of those firms that were on the previous '100 Best Companies to Work for' list but are not on the most recent list. For these portfolios the sample period starts 1 year later than indicated in Table 2. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panel B shows the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression. In these regressions monthly excess returns of these equal-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. Panel B also reports the adjusted R-squared values of the regressions.

			Panel A: Performance Measures				
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	8.18	8.15	12.93	7.79	5.37	11.96	6.42
Volatility	19.04	21.18	20.04	19.10	20.02	21.92	16.16
Sharpe	0.43	0.38	0.65	0.41	0.27	0.55	0.40
			Panel B: Factor Regressions				
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
1-F α	0.12	0.04	0.50***	-0.07	0.02	0.39	0.06
	(0.73)	(0.23)	(3.76)	(-0.36)	(0.11)	(1.21)	(0.48)
Adj. R^2	0.81	0.73	0.86	0.81	0.71	0.66	0.84
4-F α	0.24	0.09	0.62***	-0.02	0.07	0.50	0.08
	(1.48)	(0.53)	(4.71)	(-0.11)	(0.34)	(1.52)	(0.61)
Adj. R^2	0.83	0.74	0.86	0.84	0.75	0.66	0.84
5-F α	0.24	0.13	0.65***	0.22	-0.10	0.46	0.08
	(1.03)	(0.51)	(5.45)	(0.99)	(-0.43)	(1.17)	(0.44)
Adj. R^2	0.83	0.74	0.86	0.85	0.76	0.66	0.84

TABLE A11

Factor-Adjusted Returns of Value-Weighted Delisted Portfolios

This table shows the key performance measures and the regression results of value-weighted portfolios formed out of the stocks of those firms that were on the previous '100 Best Companies to Work for' list but are not on the most recent list. For these portfolios the sample period starts 1 year later than indicated in Table 2. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panel B shows the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression. In these regressions monthly excess returns of these value-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. Panel B also reports the adjusted R-squared values of the regressions.

Panel A: Performance Measures							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	9.35	6.52	9.95	4.19	3.85	9.46	5.91
Volatility	16.03	16.77	20.11	16.04	18.72	23.83	15.09
Sharpe	0.58	0.39	0.49	0.26	0.21	0.40	0.39
Panel B: Factor Regressions							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
1-F α	0.31*	0.06	0.29	-0.25	-0.04	0.13	0.06
	(1.91)	(0.25)	(1.48)	(-1.59)	(-0.18)	(0.40)	(0.53)
Adj. R^2	0.76	0.68	0.78	0.84	0.59	0.72	0.79
4-F α	0.38**	0.12	0.37*	-0.26**	0.16	0.25	0.03
	(2.27)	(0.53)	(1.69)	(-2.28)	(0.83)	(0.78)	(0.20)
Adj. R^2	0.80	0.70	0.79	0.86	0.63	0.73	0.81
5-F α	0.12	-0.09	0.50**	-0.29***	0.12	-0.04	-0.16
	(0.46)	(-0.33)	(2.39)	(-2.92)	(0.56)	(-0.11)	(-0.81)
Adj. R^2	0.80	0.70	0.79	0.86	0.63	0.73	0.82

TABLE A12

Factor-Adjusted Returns of Winsorized Equal-Weighted List Portfolios

This table shows the key performance measures and the regression results of winsorized equal-weighted portfolios formed out of the stocks of the firms on the '100 Best Companies to Work for' lists, as defined in Table 1. Portfolios are considered for the periods indicated in Table 2. Returns have been winsorized at the 10% and 90% levels. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panel B shows the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression. In these regressions monthly excess returns of these equal-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the t-statistics. Panel B also reports the adjusted R-squared values of the regressions.

Panel A: Performance Measures							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	8.43	9.30	18.25	6.12	8.37	9.66	7.51
Volatility	15.44	15.20	18.28	15.55	18.28	14.18	14.38
Sharpe	0.55	0.61	1.00	0.39	0.46	0.68	0.52
Panel B: Factor Regressions							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
1-F α	0.18	0.06	0.73***	-0.25**	0.23	0.34**	0.17
	(1.45)	(0.61)	(4.46)	(-2.07)	(1.47)	(2.21)	(1.48)
Adj. R^2	0.89	0.86	0.78	0.84	0.91	0.80	0.79
4-F α	0.28**	0.15	0.81***	-0.23**	0.23*	0.41***	0.22**
	(2.32)	(1.62)	(3.87)	(-2.00)	(1.80)	(2.73)	(2.12)
Adj. R^2	0.90	0.87	0.78	0.85	0.92	0.82	0.81
5-F α	0.08	-0.03	0.64***	-0.28***	0.15	0.18	-0.05
	(0.56)	(-0.22)	(2.66)	(-2.66)	(1.33)	(0.90)	(-0.34)
Adj. R^2	0.91	0.88	0.78	0.85	0.92	0.82	0.82

TABLE A13

Factor-Adjusted Returns of Winsorized Value-Weighted List Portfolios

This table shows the key performance measures and the regression results of winsorized value-weighted portfolios formed out of the stocks of the firms on the '100 Best Companies to Work for' lists, as defined in Table 1. Portfolios are considered for the periods indicated in Table 2. Returns have been winsorized at the 10% and 90% levels. Panel A shows annual performance measures of the portfolios: average returns, volatility, and corresponding Sharpe ratios. These performance measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panel B shows the regression results of the CAPM regression, the 4-factor regression, and the 5-factor regression. In these regressions monthly excess returns of these value-weighted portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality-minus-junk (QMJ) factor. α is the regression intercept. The returns on the Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the QMJ factor have been downloaded from the AQR website. *t*-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case that autocorrelation or heteroscedasticity was present in the regression residuals, Newey-West standard errors have been employed in the calculation of the *t*-statistics. Panel B also reports the adjusted *R*-squared values of the regressions.

Panel A: Performance Measures							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
Avg. Ret.	6.66	7.67	15.66	6.34	5.33	7.80	7.04
Volatility	14.48	13.73	16.76	13.81	19.10	14.39	14.30
Sharpe	0.46	0.56	0.93	0.46	0.28	0.54	0.49

Panel B: Factor Regressions							
	Full sample	**Europe**	**Europe-Home**	**Europe-Foreign**	**US**	**Latin America**	**Latin-Foreign**
1-F α	0.09	0.03	0.64***	-0.13	-0.02	0.22	0.17
	(0.64)	(0.20)	(2.91)	(-0.91)	(-0.13)	(1.16)	(1.12)
Adj. R^2	0.82	0.78	0.69	0.80	0.86	0.72	0.69
4-F α	0.15	0.14	0.60***	-0.12	0.07	0.25	0.19
	(1.08)	(0.98)	(2.79)	(-0.88)	(0.52)	(1.42)	(1.36)
Adj. R^2	0.85	0.82	0.72	0.83	0.88	0.75	0.72
5-F α	-0.15	-0.26*	0.57**	-0.28**	-0.01	-0.10	-0.20
	(-0.93)	(-1.66)	(2.30)	(-2.03)	(-0.09)	(-0.49)	(-1.00)
Adj. R^2	0.86	0.84	0.72	0.84	0.88	0.76	0.74

A4. Results Corporate Sustainability Assessment (CSA) Sample

FIGURE A8

Performance of Global Employee Satisfaction (ES) Portfolios

This figure shows the value-weighted cumulative compound excess returns of 1 dollar being invested in the global ES portfolios at the end of September 2003. Portfolios are re-balanced on a yearly basis and held until December 2015. Bottom is the portfolio containing the stocks in the lowest ES decile, while Top is the portfolio containing the stocks in the highest ES decile. Universe is the value-weighted portfolio of all stocks in the entire CSA universe. The cumulative compound returns are calculated as $(1 + r_1)(1 + r_2) \ldots (1 + r_T)$.

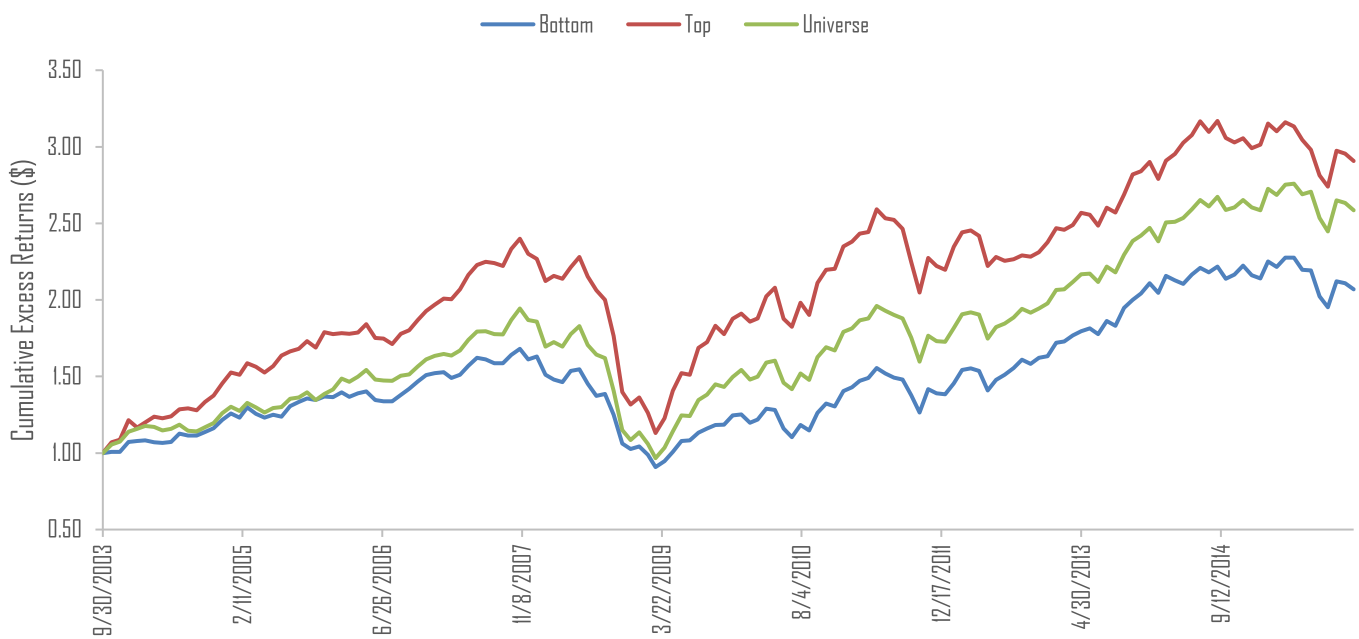

FIGURE A9

Performance of North American Employee Satisfaction (ES) Portfolios

This figure shows the value-weighted cumulative compound excess returns of 1 dollar being invested in the North American ES portfolios at the end of September 2003. Portfolios are re-balanced on a yearly basis and held until December 2015. Bottom is the portfolio containing the stocks in the lowest ES decile, while Top is the portfolio containing the stocks in the highest ES decile. Universe is the value-weighted portfolio of all stocks in the North American CSA universe. The cumulative compound returns are calculated as $(1+r_1)(1+r_2)\ .\ \ .\ \ .(1+\ r_T)$.

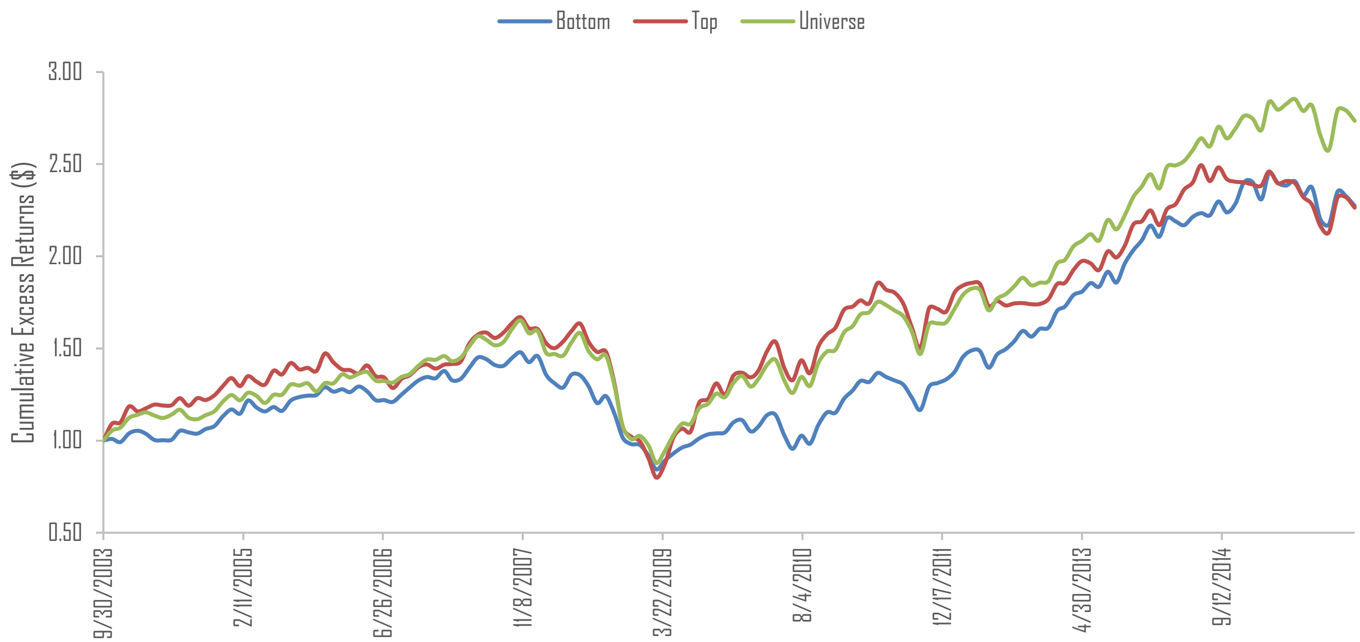

FIGURE A10

Performance of North American Sector-Neutral Employee Satisfaction (ES) Portfolios

This figure shows the value-weighted cumulative compound excess returns of 1 dollar being invested in the North American sector-neutral ES portfolios at the end of September 2003. Portfolios are re-balanced on a yearly basis and held until December 2015. Bottom is the portfolio containing the stocks in the lowest ES decile, while Top is the portfolio containing the stocks in the highest ES decile. Universe is the value-weighted portfolio of all stocks in the North American CSA universe. The cumulative compound returns are calculated as $(1 + r_1)(1 + r_2) \ldots (1 + r_T)$.

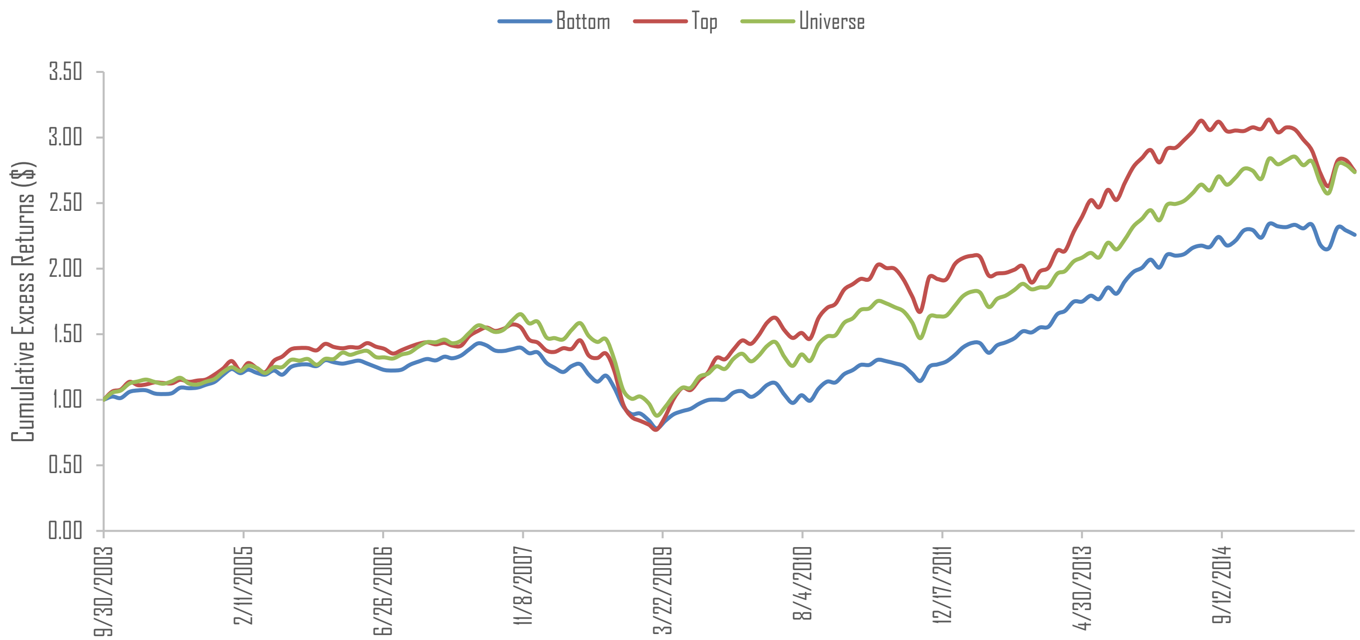

TABLE A14

Factor-Adjusted Returns of Global Employee Satisfaction (ES) Decile Portfolios

This table presents performance measures and regression results of global value-weighted decile portfolios, sorted on ES. Bottom contains the stocks with lowest ES levels, Top contains highest ES level stocks. Universe is the value-weighted portfolio of all stocks in the CSA universe. Portfolio returns are available for October 2003 - December 2015. Panel A shows annual performance measures. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM, 4-factor, and 5-factor regressions, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality (Q) factor. α is the regression intercept. The returns on the global Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the Q factor have been calculated from the entire CSA universe. *t*-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding *p*-value, and the *p*-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	7.16	8.00	6.17	7.94	7.41	9.94	8.29	8.58	9.55	10.58	3.21	9.29		0.29
Volatility	14.00	15.26	16.55	15.18	16.13	14.25	14.62	15.30	16.14	16.40	7.36	14.99		
Sharpe	0.51	0.52	0.37	0.52	0.46	0.70	0.57	0.56	0.59	0.65	0.44	0.62		

Panel B: CAPM

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.03	0.03	-0.14	0.04	-0.04	0.24*	0.09	0.10	0.12	0.20	0.17	0.88	0.56	0.01
	(0.37)	(0.35)	(-1.07)	(0.31)	(-0.32)	(1.78)	(1.12)	(0.74)	(1.17)	(1.55)	(1.01)			
β_{Mkt}	0.85***	0.95***	1.00***	0.93***	0.99***	0.86***	0.89***	0.92***	1.00***	1.00***	0.15***			
Adj. R^2	0.89	0.93	0.89	0.90	0.91	0.88	0.90	0.87	0.91	0.89	0.09			

Panel C: 4-Factor Regressions

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.00	0.06	-0.18	0.05	-0.05	0.23*	0.02	0.04	0.13	0.23	0.24	1.07	0.39	0.00
	(-0.02)	(1.03)	(-1.48)	(0.36)	(-0.39)	(1.94)	(0.20)	(0.30)	(1.15)	(1.58)	(1.45)			
β_{Mkt}	0.90***	0.96***	1.05***	0.92***	1.00***	0.87***	0.94***	0.94***	1.01***	0.98***	0.08*			
β_{SMB}	-0.26***	-0.06	-0.07	-0.08	0.02	-0.24***	-0.29***	-0.17	-0.16**	0.01	0.27**			
β_{HML}	-0.23***	-0.20***	-0.28**	0.08	-0.10	0.02	-0.11	0.02	-0.13	0.04	0.27**			
β_{MOM}	0.07**	-0.03	0.07	0.00	0.01	0.02	0.13***	0.10*	0.00	-0.05	-0.13**			
Adj. R^2	0.90	0.93	0.90	0.89	0.90	0.88	0.92	0.87	0.92	0.89	0.19			

Panel D: 5-Factor Regressions (Includes Quality Factor)

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.00	0.06	-0.10	0.08	-0.02	0.31**	0.07	0.09	0.18	0.32**	0.32*	1.40	0.19	0.00
	(0.03)	(1.05)	(-0.75)	(0.64)	(-0.16)	(2.54)	(0.68)	(0.64)	(1.52)	(2.26)	(1.95)			
β_{Mkt}	0.90***	0.96***	1.01***	0.90***	0.99***	0.83***	0.92***	0.91***	0.99***	0.93***	0.04			
β_{SMB}	-0.26***	-0.07	-0.15*	-0.12*	-0.01	-0.31***	-0.34***	-0.22**	-0.20**	-0.08	0.19*			
β_{HML}	-0.23***	-0.20***	-0.29***	0.07	-0.10	0.01	-0.11	0.02	-0.13	0.03	0.26**			
β_{MOM}	0.07**	-0.02	0.09**	0.01	0.02	0.05	0.14***	0.12**	0.01	-0.03	-0.10*			
β_{Q}	-0.02	-0.03	-0.28***	-0.12	-0.09	-0.24***	-0.17**	-0.18*	-0.16	-0.30**	-0.28**			
Adj. R^2	0.90	0.93	0.90	0.90	0.90	0.89	0.92	0.87	0.92	0.90	0.22			

TABLE A15

Factor-Adjusted Returns of North American Employee Satisfaction (ES) Decile Portfolios

This table presents performance measures and regression results of North American value-weighted decile portfolios, sorted on ES. Bottom contains the stocks with lowest ES levels, Top contains highest ES level stocks. Universe is the value-weighted portfolio of all stocks in the North American CSA universe. Portfolio returns are available for October 2003 - December 2015. Panel A shows annual performance measures. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM, 4-factor, and 5-factor regressions, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality (Q) factor. α is the regression intercept. The returns on the global Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the Q factor have been calculated from the North American CSA universe. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding p-value, and the p-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	7.90	6.82	8.48	7.22	5.69	10.70	11.68	7.51	8.55	8.36	0.43	9.64		0.47
Volatility	13.43	16.21	15.98	18.08	18.11	14.73	13.36	14.27	16.58	16.57	9.90	14.05		
Sharpe	0.59	0.42	0.53	0.40	0.31	0.73	0.87	0.53	0.52	0.50	0.04	0.69		

Panel B: CAPM

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.08	-0.14	0.01	-0.17	-0.29	0.34	0.40***	0.02	0.01	-0.02	-0.11	0.87	0.56	1.00
	(0.61)	(-1.27)	(0.06)	(-0.92)	(-1.59)	(1.45)	(2.85)	(0.14)	(0.05)	(-0.15)	(-0.49)			
β_{Mkt}	0.82***	1.02***	1.00***	1.12***	1.12***	0.76***	0.78***	0.87***	1.00***	1.03***	0.21*			
Adj. R^2	0.80	0.85	0.83	0.82	0.82	0.57	0.73	0.80	0.78	0.83	0.09			

Panel C: 4-Factor Regressions

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	-0.01	-0.13	0.00	-0.13	-0.26*	0.35*	0.31**	0.01	-0.04	0.00	0.02	0.72	0.71	0.98
	(-0.11)	(-1.30)	(0.02)	(-0.73)	(-1.72)	(1.77)	(2.12)	(0.14)	(-0.18)	(0.02)	(0.08)			
β_{Mkt}	0.94***	1.02***	1.01***	1.10***	1.11***	0.79***	0.86***	0.94***	1.02***	1.03***	0.10			
β_{SMB}	-0.34***	0.03	0.02	0.08	-0.02	-0.17	-0.26***	-0.31***	-0.06	-0.13	0.22**			
β_{HML}	-0.13**	-0.09	-0.15	-0.16	-0.05	-0.09	0.10	-0.07	0.11	0.05	0.18			
β_{MOM}	0.15***	-0.01	0.00	-0.10	-0.10*	-0.08	0.17***	-0.06	0.12	-0.09*	-0.24***			
Adj. R^2	0.85	0.85	0.83	0.82	0.82	0.57	0.77	0.83	0.79	0.84	0.22			

Panel D: 5-Factor Regressions (Includes Quality Factor)

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	-0.03	-0.15	0.06	-0.07	-0.27*	0.35	0.33**	0.07	-0.04	0.03	0.06	0.80	0.63	1.00
	(-0.22)	(-0.96)	(0.39)	(-0.41)	(-1.91)	(1.47)	(2.10)	(0.78)	(-0.18)	(0.19)	(0.27)			
β_{Mkt}	0.95***	1.03***	0.98***	1.06***	1.12***	0.79***	0.85***	0.90***	1.03***	1.02***	0.07			
β_{SMB}	-0.33***	0.03	-0.01	0.04	-0.01	-0.17	-0.27***	-0.35***	-0.06	-0.14*	0.19**			
β_{HML}	-0.11*	-0.07	-0.21**	-0.23**	-0.03	-0.08	0.08	-0.14*	0.11	0.02	0.13			
β_{MOM}	0.15***	-0.01	0.01	-0.09	-0.10*	-0.08	0.18***	-0.06*	0.12	-0.09*	-0.23***			
β_{Q}	0.08	0.07	-0.31***	-0.34*	0.10	0.03	-0.10	-0.32***	0.02	-0.14	-0.22*			
Adj. R^2	0.85	0.85	0.85	0.84	0.82	0.57	0.77	0.85	0.78	0.84	0.24			

TABLE A16

Factor-Adjusted Returns of North American Sector-Neutral Employee Satisfaction (ES) Decile Portfolios

This table presents performance measures and regression results of North American sector-neutral value-weighted decile portfolios, sorted on ES. Bottom contains the stocks with lowest ES levels, Top contains highest ES level stocks. Universe is the value-weighted portfolio of all stocks in the North American CSA universe. Portfolio returns are available for October 2003 - December 2015. Panel A shows annual performance measures. These measures are first calculated for monthly excess returns (in percentage terms) and then annualized. Panels B, C, D show the regression results of the CAPM, 4-factor, and 5-factor regressions, respectively. Monthly excess returns of these portfolios are regressed on the market (Mkt) factor, the size (SMB) factor, the value (HML) factor, the momentum (MOM) factor, and the quality (Q) factor. α is the regression intercept. The returns on the global Mkt, SMB, HML, and MOM factors have been downloaded from the website of Kenneth French. The returns on the Q factor have been calculated from the North American CSA universe. t-statistics are shown in the brackets. '***', '**', and '*' indicate significance at the 1%, 5%, and 10% levels, respectively. In the case of residual autocorrelation or heteroscedasticity, Newey-West standard errors are used. The last three columns show the GRS test statistic, the corresponding p-value, and the p-value of the Wolf-Romano (WR) test.

Panel A: Performance Measures

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	Universe		*p*-value WR
Avg. Ret.	7.68	8.02	8.85	8.42	7.77	7.84	9.02	7.26	8.73	9.97	2.14	9.64		0.57
Volatility	12.25	15.29	14.79	18.10	17.61	14.70	13.71	14.98	14.49	15.97	8.77	14.05		
Sharpe	0.63	0.52	0.60	0.47	0.44	0.53	0.66	0.48	0.60	0.62	0.24	0.69		

Panel B: CAPM

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.09	-0.01	0.08	-0.09	-0.12	0.06	0.16	-0.06	0.08	0.13	0.04	0.49	0.90	1.00
	(0.86)	(-0.13)	(0.88)	(-0.76)	(-0.69)	(0.29)	(1.07)	(-0.54)	(0.62)	(0.76)	(0.19)			
β_{Mkt}	0.78***	0.97***	0.94***	1.14***	1.10***	0.85***	0.84***	0.96***	0.92***	0.98***	0.20***			
Adj. R^2	0.87	0.87	0.87	0.86	0.84	0.71	0.81	0.88	0.86	0.81	0.11			

Panel C: 4-Factor Regressions

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.05	-0.01	0.07	-0.07	-0.06	0.03	0.12	-0.06	0.07	0.22	0.17	0.41	0.94	1.00
	(0.50)	(-0.15)	(0.84)	(-0.55)	(-0.40)	(0.16)	(0.85)	(-0.55)	(0.53)	(1.38)	(0.94)			
β_{Mkt}	0.85***	0.97***	0.93***	1.12***	1.06***	0.86***	0.82***	0.99***	0.93***	0.93***	0.08*			
β_{SMB}	-0.24***	0.11	0.13	0.17**	0.12*	0.07	0.19***	-0.08	0.01	0.09	0.33***			
β_{HML}	-0.07	-0.10**	-0.13	-0.23***	-0.10	-0.13	0.10	-0.13	-0.05	-0.10	-0.03			
β_{MOM}	0.05	0.01	0.03	-0.05	-0.13	0.07	0.14	-0.03	0.02	-0.20	-0.25			
Adj. R^2	0.89	0.88	0.87	0.86	0.85	0.72	0.83	0.88	0.86	0.83	0.27			

Panel D: 5-Factor Regressions (Includes Quality Factor)

	Bottom	P2	P3	P4	P5	P6	P7	P8	P9	Top	Top-Bottom	GRS	*p*-value	*p*-value WR
α	0.03	-0.01	0.09	-0.04	-0.05	0.07	0.12	-0.07	0.06	0.24	0.21	0.42	0.94	1.00
	(0.28)	(-0.15)	(1.05)	(-0.32)	(-0.35)	(0.37)	(0.86)	(-0.58)	(0.47)	(1.47)	(1.16)			
β_{Mkt}	0.86***	0.97***	0.92***	1.10***	1.05***	0.84***	0.81***	0.99***	0.93***	0.92***	0.06			
β_{SMB}	-0.23***	0.11	0.12	0.15	0.12*	0.05	0.18***	-0.08	0.02	0.08	0.31***			
β_{HML}	-0.05	-0.10*	-0.16***	-0.27	-0.11	-0.18	0.10	-0.13	-0.04	-0.12	-0.07			
β_{MOM}	0.04*	0.01	0.03	-0.04	-0.13***	0.07	0.14***	-0.03	0.02	-0.20***	-0.25***			
β_{Q}	0.12*	0.00	-0.12	-0.20	-0.06	-0.23**	-0.01	0.02	0.05	-0.09	-0.21**			
Adj. R^2	0.89	0.88	0.88	0.87	0.85	0.73	0.83	0.88	0.86	0.83	0.29			

A5. Algorithms

ALGORITHM A1

Critical Value Distribution Calculation of Wolf and Romano's (2013) Cons Test

- Generate bootstrap differential series by randomly picking 5 moving blocks of differentials, resulting in 60 observations of differential sets: $\{\boldsymbol{d}_1^*,\ \boldsymbol{d}_2^*,\ \ldots,\ \boldsymbol{d}_{T=60}^*\}$, with $\boldsymbol{d}_t^* = [d_{t,1}^*\ d_{t,2}^*\ \ldots\ d_{t,9}^*]$
- Using this bootstrap data, calculate statistics $\hat{\Delta}_{T,i}^*$ and $\hat{\sigma}_{T,i}^*$ for $i = 1, \ldots, 9$, making sure to use HAC standard errors when serial correlation is present in the bootstrap differential series
- Compute $t_{T,i}^*$ for $i = 1, \ldots, 9$ using the following formula:

  $$t_{T,i}^* = \frac{\hat{\Delta}_{T,i}^* - \hat{\Delta}_{T,i} + \Delta_{0,i}}{\hat{\sigma}_{T,i}^*}$$
- Get the final test statistic for this set of bootstrapped differentials as $t_T^{min,*} = min_i t_{T,i}$
- Repeat the above steps 1000 times, resulting in statistics $t_{T,1}^{min,*}, t_{T,2}^{min,*}, \ldots, t_{T,1000}^{min,*}$
- The distribution of these statistics $t_{T,1}^{min,*}, t_{T,2}^{min,*}, \ldots, t_{T,1000}^{min,*}$ is then the bootstrap approximation for the sampling distribution of test statistic t_T^{min} under the null hypothesis and thus I can calculate the corresponding p-value of t_T^{min}

ALGORITHM A2

Pathwise Coordinate Descent Algorithm for Pen-FM Estimators

- Fix the initial values at the mean values of $\hat{\boldsymbol{\beta}}$, denote this as $\tilde{\boldsymbol{\lambda}}$
- Pick a factor (or the intercept) $i \in [1, \ldots, K]$ and collect the remaining factors (possibly including the intercept) in $j = [1, \ldots, K] \neq i$
- Rewrite the overall loss function as

  $$L = [\,\bar{\boldsymbol{R}} - \hat{\boldsymbol{\beta}}_{\boldsymbol{i}}'\lambda_i - \hat{\boldsymbol{\beta}}'\tilde{\boldsymbol{\lambda}}_{\boldsymbol{j}}]'[\,\bar{\boldsymbol{R}} - \hat{\boldsymbol{\beta}}'\boldsymbol{\lambda}] + \eta_{\boldsymbol{T}} \left(\sum_{j=1}^{K} \frac{1}{\|\hat{\boldsymbol{\beta}}_j\|_{\boldsymbol{1}}^{d}} |\tilde{\lambda}_j| + \frac{1}{\|\hat{\boldsymbol{\beta}}_i\|_{\boldsymbol{1}}^{d}} |\lambda_i| \right)$$
- Minimize L with respect to λ_i and update the initial values $\tilde{\boldsymbol{\lambda}}$ with this estimate
- Repeat this update for all elements of $\tilde{\boldsymbol{\lambda}}$
- Repeat the above steps until convergence is reached, where convergence is defined as $\max(|\tilde{\boldsymbol{\lambda}}_{\boldsymbol{old}} - \tilde{\boldsymbol{\lambda}}_{\boldsymbol{new}}|) \leq 0.00001)$

ALGORITHM A3

Critical Value Distribution Calculation of Pen-FM Test Statistic ($\boldsymbol{B_T}$)

- Pick 200 stocks out of the total sample of N stocks and separate their values for $\widehat{\boldsymbol{\beta}}$ and $\overline{\boldsymbol{R}}$ and first pass residuals
- Draw random error matrix $\boldsymbol{\Psi} = \begin{bmatrix} \boldsymbol{\Psi_R}' \\ \boldsymbol{\Psi_\beta}' \end{bmatrix} \sim N(\boldsymbol{0}, \boldsymbol{V})$

  with $\boldsymbol{V} = \boldsymbol{Q} \otimes \boldsymbol{\Omega}$, where $\boldsymbol{\Omega}$ is the sample covariance matrix of the first pass residuals,

  $\boldsymbol{Q} = \begin{pmatrix} 1 & \overline{\boldsymbol{F}}' \\ \overline{\boldsymbol{F}} & \widehat{\boldsymbol{V}}_{\boldsymbol{ff}} + \overline{\boldsymbol{F}}\overline{\boldsymbol{F}}' \end{pmatrix}$ with $\overline{\boldsymbol{F}}$ the sample mean of all factors considered over time, and $\widehat{\boldsymbol{V}}_{\boldsymbol{ff}}$ the sample covariance matrix of the factors
- Compute simulated values for $\widehat{\boldsymbol{\beta}}^*$ and $\overline{\boldsymbol{R}}^*$ using the following formulas:

  $\widehat{\boldsymbol{\beta}}^* = \widehat{\boldsymbol{\beta}} + \frac{1}{\sqrt{T}}\boldsymbol{\Psi_\beta}$

  $\overline{\boldsymbol{R}}^* = \overline{\boldsymbol{R}} + \frac{1}{\sqrt{T}}\boldsymbol{\Psi_R}$
- Using the path wise coordinate descent algorithm outlined in Algorithm A2, solve for $\widehat{\boldsymbol{\lambda}}^*_{\boldsymbol{pen}}$ in:

  $\widehat{\boldsymbol{\lambda}}^*_{\boldsymbol{pen}} = min_\lambda \left[\overline{\boldsymbol{R}}^* - \widehat{\boldsymbol{\beta}}^{*\prime}\boldsymbol{\lambda}\right]' \left[\overline{\boldsymbol{R}}^* - \widehat{\boldsymbol{\beta}}^{*\prime}\boldsymbol{\lambda}\right] + \eta_{\boldsymbol{T}} \sum_{j=1}^{K} \frac{1}{\left\|\beta_j^*\right\|_{\boldsymbol{1}}^{d}} |\lambda_{\boldsymbol{j}}|$
- Calculate critical value statistic $\boldsymbol{B_T^*}$:

  $\boldsymbol{B_T^*} = \sqrt{T}\left(\widehat{\boldsymbol{\lambda}}^*_{\boldsymbol{pen}} - \widehat{\boldsymbol{\lambda}}_{\boldsymbol{pen}}\right)$
- Repeat the above procedure 10,000 times to obtain a set of vectors for $\boldsymbol{B_T^*}$: $\left\{\boldsymbol{B^*_{T,1}}, \boldsymbol{B^*_{T,2}}, \ldots, \boldsymbol{B^*_{T,10,000}}\right\}$
- This set of values for each element of $\boldsymbol{B_T^*}$, separately, is then an approximation to the theoretical distribution of the elements of $\boldsymbol{B_T}$ and one may use it to calculate a *p*-values for the individual elements of $\boldsymbol{B_T}$