A Portfolio Strategy Using Glassdoor's Business Outlook Ratings

Derek Snow

2016

Table of Contents

List of Tables

List of Figures

Acknowledgements

I would like to thank my supervisor, Dr. Helen Lu for her valuable guidance and feedback. Her support, patience, enthusiasm and immense knowledge have guided me throughout this research process. I also want to thank Dr. Paul Greetsma for his invaluable coding session. Last, but not least, thanks to my parents for their support and love.

Abstract

I document that a simple portfolio strategy, selling stocks with worsening business outlook, provides significant abnormal returns. I construct a portfolio of firms one day after they experience a change in business outlook for all sample trading days. Over the sample of 56 consecutive trading days, 3,502 adjustments in business outlook took place. The daily average abnormal return, produced by shorting a worsening portfolio of firms, is 0.232 %. The accumulated raw return of this portfolio over the sample period is 4.3%. I show that better returns can be obtained by forming portfolios using large stocks. I also show that a long-short portfolio, buying large improving-firms and selling large worsening-firms produce significant abnormal profits with daily portfolio rebalancing and a timely response to a change in outlook. Moreover, both legs, on average, show comparable size and book-to-market characteristics. I further test for a delayed reaction from investors after the adjustments in business outlook takes place and also introduce an overlapping rebalancing strategy, neither of which produce significant returns. The main findings also survive various robustness tests. The purpose of this study is two-fold. I, not only show the opportunity for a profitable portfolio strategy, but I also look at the implications that significant portfolio returns have on the usefulness and quality of employee-sourced data.

1 Introduction

Various financial and journalistic sites, such as the Wall Street Journal, Financial Times, Fortune, Washington Post, Bloomberg and even NZ Herald, have examined the use of Glassdoor metrics and firm data to create profitable investment portfolios (2015). MaryJo Fitzgerald (2016), Corporate Affairs Manager at Glassdoor, says that they “hear from and talk to investors who use the data on our site all the time”. BlackRock, the world’s largest asset manager, has also been reported to use Glassdoor data for investment decisions (Crowe, 2016; Rose, 2016).

Information on Glassdoor is produced in real-time and is forward-looking. Employees are asked whether they expect their firms’ next six months’ business outlook to worsen, improve or remain the same. This study investigates all the business outlook adjustments (BOAs) that Fortune 1000 firms[1] experienced over a timeframe of 56 consecutive trading days. I have identified 3,502 observations that consists of 1,733 upward changes in business outlook and 1,769 downward changes in business outlook from the 18th of May to the 8th of August 2016.

Until recently, investors had little data on employees’ perspectives of their firms. However, innovations such as social media and employee review sites have started to open this previous black-box to the general public. Traditional methods to gauge business outlook, such as analysing executives’ public announcements and behaviour, inquiring about the state of a company via survey and scrutinizing annual reports and company disclosures are slow and backward-looking. These measures do not originate from the frontline of the firm. This study seeks to overcome these issues by assembling a novel social media dataset that captures the level and change in employee’s perception of a company’s business outlook in real-time.

[1] As identified in 2015. The sample excludes privately traded, depreciated, acquired, merged, bankrupted, partnership, pension and mutual fund firms.

A handful of corporate finance (e.g. Huang, Li, Meschke and Guthriem 2015; Moniz, 2016) and management (e.g., O'Really, Caldwell, Chatman and Doerrm 2014) papers have begun to make use of Glassdoor as a data source, my study is the foremost contributor in using Glassdoor's business outlook datasets. My methodology is to track changes in business outlook from the perspective of the firm's main stakeholders, namely their employees and to see whether this information has any value in constructing investment portfolios. I gathered the data by web crawling and scraping over Glassdoor[2] and extracting dynamic outlook data on a day-to-day basis. This information is publicly available and free to access.

In a published research report it was shown that an investment portfolio using Glassdoor's rankings of the best place to work, as constructed from employee input, between 2009 and 2014, outperformed the overall market by 115.6%. That is 31% more than Fortunes "Best Companies to Work for" over that time (Chamberlain, 2015). This can be an initial indication of the usefulness of employee information.

To investigate if investors respond to this changes in business outlook and to see whether a profitable investment strategy exists, I construct a benchmark portfolio to test the portfolio returns the day following the announcement using daily rebalancing and then I also test for delayed investor response as well as construct portfolios with less rebalancing. I further introduce size adjusted portfolios and show that long-short portfolios for large firms are profitable, primarily from the short leg.

A change in business outlook might occur as a result of company improvements that are publicly known and reflected in the stock price. It is also possible that business outlook adjustments contain valuable insider information possessed by employees but unknown to the market. Adjustments in outlook can therefore occur as a result of internal considerations and

[2] www.glassdoor.com

events that are not yet known to the market. I believe that real-time adjustments in outlook helps to level out asymmetric information between the firm and shareholders.

For the purpose of this study, I classify changes in outlook as any change greater than or equal to 1 percentage point (pp) for both a downward and upward change in outlook. What makes this particularly useful is the knowledge that at least one person has come forward with the believe that business outlook has worsened. See figure A1, in the attachments, to understand what inputs employees provide. In this study, I expect a portfolio of worsening and improving outlook firms to produce abnormal returns significantly different to zero. I also expect a long-short portfolio to produce returns significantly different to zero.

When employees give their opinion of future business outlook, it can either be in relation to an event, a contract or any other happening that occurred at that time or is expected to happen in the future. Employees are not forced to give their opinion of a firm's future business outlook. They do this voluntarily and if employees are concerned with the state of a company and give their input on Glassdoor, then it is likely to be something of importance. I show that the data I obtained is mostly symmetrical with a few outliers, see figure 3 in the main text.

The day after the BOA, the full-sample portfolio experienced significant daily abnormal returns of 0.232%. This result provides evidence that the market is not fully efficient. Because firm news and disclosures could potentially be driving the changes in business outlook, I have controlled for firm financial news by excluding observations that fell around 3 days of earnings announcements. The S&P 500 benchmark has performed well over the period, experiencing a 10% increase. To validate the results of my study I have incorporated strong robustness tests. On each day in the sample period, there is a minimum of 11 firms that experiences an adjustment in business outlook, this allows me to easily rebalance the portfolios one day after the change occurred, by only incorporating firms that have experienced a change in outlook on that day.

I have also performed a few other tests such as, incorporating an overlapping rebalancing strategy (4, 7, 10 and 20 days), segmenting firms in sized portfolios, calculating the significance of long-short portfolios as well as constructing hypothetical portfolios to test the supposed returns of portfolios in advance of the change in companies' business outlook to see if insiders can, on average, take advantage of the event that underlies the change in outlook or if there is some other event driving the change apart from investors' response to a change in outlook. A portfolio of firms that report a positive change in business outlook experienced a 1.8 % raw return over the sample period and a portfolio of firms that report a negative change in business outlook experienced a 4.3% decrease in raw returns. The signs of these portfolios are as hypothesised, but they show limited significance. After controlling for risk, the portfolios do show significance.

To illustrate the importance of portfolio composition and to identify the level of noise in the study, we performed a robustness exercise by replicating the above steps for equal weighted portfolios. This led to a few changes, most notably a change in sign for the improved outlook portfolio. As a result, I incorporate portfolio characteristics to identify whether size might explain the difference between the improved and worsening outlook return for value-weighted and equal-weighted portfolios. Lastly, I have incorporated robustness tests by checking for auto-correlation, removing outliers with winsorising and excluding subsets of data that might bias my results.

Under the efficiency market viewpoint, publicly available information should already be incorporated in current prices. Abnormal returns in this study would contradict this view. This study contributes to literature by identifying whether employee's candid and anonymous assessments of their firms' business outlook can affect the immediate shareholder value and hence allow for the construction of a profitable investment portfolio by making use of a public data set.

2 Literature

Given the uniqueness of this study, I have to probe into various areas of literature to understand and form an expectation for my research. This study is related to the literature that looks at the impact of social media on firm performance. This paper is also related to the works on the dissemination of information. Finally, my research is somewhat related in answering the question as to whether employees collectively have 'inside' information, which can be used to construct profitable investment portfolios.

2.1 Social Media Channels

Prior research shows that the low cost of online publishing and rise of discussion forums and niche social media websites are supplementing and some cases supplanting the traditional Wall Street information ecosystem (Costa, 2010). Recent studies show that at least one in three individuals in the US relies on social media outlets for investment advice (Lacy et al., 2016). With the advent of social-media, we have seen firms opening up their engagement with the public and generally offering more transparency into their operations (Bonson, Flores, 2011). More recently, the SEC has issued guidance that specifically allows for the use of social media to disseminate company news [3]. However, due to the interactive nature of social media platforms, firms don't have as much control over some of the ancillaries and feedback functionalities (Miller, Skinner, 2015).

Jame et al. (2016) shows, with the use of social media, that crowdsourced earnings estimates, as provided for by Estimize, can generate significant two-day size-adjusted returns from consensus revisions in earnings. They have shown that such a service is a useful supplementary source of information in capital markets. Other research shows the effect

[3] http://www.sec.gov/News/PressRelease/Detail/PressRelease/1365171513574#.VM9_R3u8rfc

‘followers’ and ‘likes’ can have on a firm's share value (Paniagua et al. 2014). I similarly show that Glassdoor data can be useful in generating returns.

These social platforms need not necessarily be investor-run such as is the case with Seeking Alpha and StockTwist[4], they can also be employee focused such as Glassdoor and PayScale, which allows for extensive data to be gathered from a source inside the firm, namely, the employees. These metrics include, among other things employees’ perspective on a firms’ business outlook.

2.2 Employee Knowledge

Babenko and Sen (2014) shows that employees perspectives and opinions matter by investigating the aggregate purchases of company stocks by lower level employees. They show that employees purchases predict future stock returns. An interesting study by Cohen et al. (2012), shows that the trades of local non-senior opportunistic traders have the most predictability of future firm events. In my research, I find results that are fairly consistent with Babenko and Sen (2014) and show that profitable investment portfolios can be constructed by using employees opinions of a firms’ changing business outlook.

Baker and Haslem (1973) show that individual investors use many different factors in the analysis of common stock. They argue that financial statements and profit forecasts are not sufficient and that investors need other evidence such as information on a firm’s business outlook and the future condition of the industry. Tainer (2006) shows, with the use a business outlook survey (Philadelphia Fed’s BOS), that a decrease in business outlook is correlated with equity price decline. In my study I would use a timelier measure of business outlook to see if investors can profit from having an early glimpse into business outlook, without having to rely on surveys, annual reports or earnings announcements.

[4] www.seekingalpha.com, www.stocktwist.com

2.3 Information Dissemination

Kothari et al. (2009) shows that managers defer the dissemination of bad news and accelerate the revelation of good news. Research also shows that the media identifies one third of events such as frauds before they get announced by the firm (2006). Glassdoor provides a quicker dissemination of bad news. Employees are not necessarily held to higher standards when it comes to disseminating information of a firm's business outlook. In this study I would identify whether employees' perspectives on business outlook matters and whether investors can profit from this timely information.

The arrival of social media platforms such as Glassdoor means that many more actors can make their views about the firm known and disseminate those views widely, potentially creating adverse consequences for firms (Miller, Skinner 2015). In addition to providing more sources of news, some observers argue that proliferation of social media will reduce interest in and resources available for more conventional media, weakening its role, while social media becomes more important (Lau and Wydick, 2014).

Saxton and Gregory (2013) have shown that financial blogging activity diminishes harmful information asymmetries between key market investors. Social media produce a crucial levelling of a firm's informational environment. Platforms such as Glassdoor have a democratising impact on traditional structure governing information. Levitt and Dubner (2005) claims that, "Information asymmetries everywhere have been mortally wounded by the Internet". I have experienced similar results and show that investors react to a change in business outlook.

2.4 Contribution and Hypothesis

Studies such as mine, forms part of an important new strand in literature, where the curtains are raised and visibility gained inside the internal operations of organisations.

Research up and till now has been focused on the extent to which investors make their views known or firms as a means of public disclosure (Jame, 2016, Paniagua et al. 2014, Loughlin & Harnisch 2014). Research are yet to focus on the effect employees or investor-employees have in the dissemination of their views.

Prior research in corporate finance (e.g. Huang, Li, Meschke and Guthriem 2015; Moniz, 2016) and management (e.g., O'Really, Caldwell, Chatman and Doerrm 2014) have just begun to make use of Glassdoor as a data source, I am the foremost contributor in making use of their business outlook metric. This research contributes to two major areas of inquiry. First this study adds to the extensive literature on inside knowledge, by showing that information known by employees, "insiders", can be used to form profitable investment strategies. The study also provides a novel contribution to literature by being the first to investigate the effect of a real-time business outlook change on future returns.

These business outlook adjustments (BOAs) can occur as a result of company improvements that are publicly known, but unknown to me, and thus it might affect the stock price or cause a run-up before the change in outlook. My measure might therefore merely pick up these events. On the other hand, these adjustments could also signal new information to the market.

The study's main hypothesis is that:

H_1: Forming long and short portfolios by buying firms with improving and selling firms with decreasing business outlook produces significant abnormal returns.

3 Data and Sample Collection

The measure for business outlook is obtained from Glassdoor. It is defined as employee's rating of a company's next 6 months' business outlook. This measure is dynamic over the sample period. Forming and shorting portfolios of companies that experience a decrease in business outlook has been found to produce significant returns around the public disclosure of a change in the business outlook rating on Glassdoor.

Figure 1: *Observations and Sample Schematic*

2015 Fortune 1000 Firms: 1000

Publicly Traded Firms: 661

Number of companies that experienced a change in outlook: 635

Number of outlook changes (BOA): 3502

Upwards Change
1733

Large Firms
918

Small Firms
735

Downward Change
1769

Large Firms
864

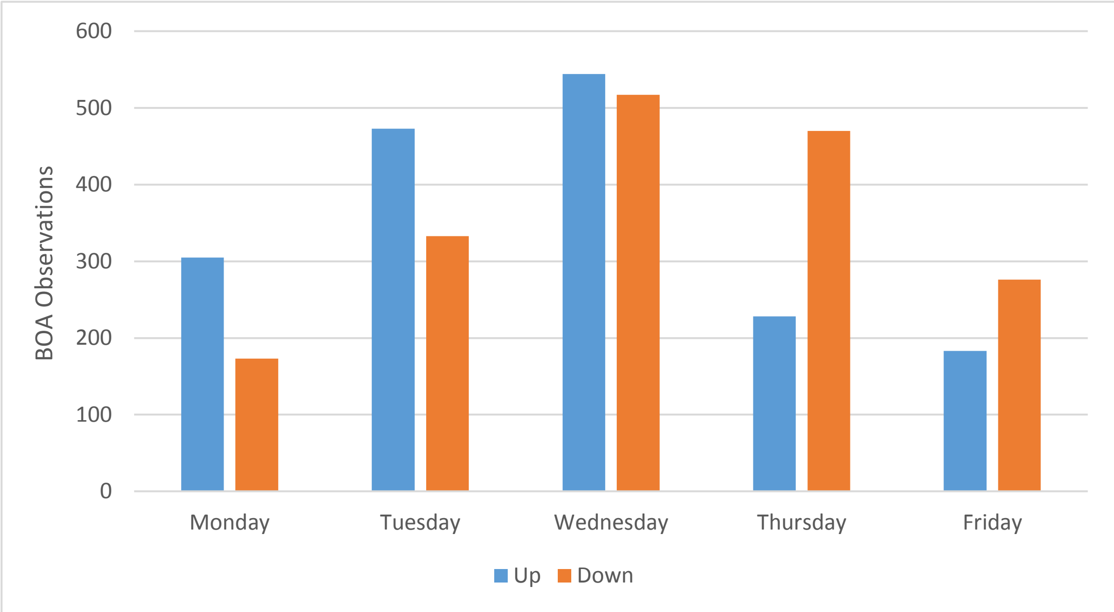
Small Firms
822

In this study I was able to identify 635 firms after matching three datasets being, the fortune 1000 list of 2015[5], Glassdoor's public business outlook data and Reuter's DataStream for market cap and price-to-book and returns data. The reason for the majority of the decrease in sample size is due to the inability to obtain pricing information for private companies, mutual funds, pension funds, government agencies and partnerships. Two other contributors to the decrease in sample are, first, the fact that 18 firms (3%) of the original sample did not experience a change in business outlook over our sample period and, second, the procedure of excluding 8 firms (1%) that had earnings announcements in the 3-day window (-1, 1) around the BOA. The fortune 1000 firms were chosen due to the importance of selecting companies with many employees. This is required so that there is enough employee input so that the metrics, such as employee's perspective of their firms' next 6 months' business outlook, as reflected by Glassdoor, are less noisy. The fortune 1000 list is constructed based on a firm's level of revenue and this is ostensibly related with more employees and more outlook changes.

The business outlook measure was taken for 56 trading days from the 18th of may 2016 to the 8th of August 2016 after market close, New York time (GMT-4) at 9:30 pm, serendipitously after normal and after-hours trading. The adjustments in business outlook takes place from 9:30 the previous day in real time up and till 9:30 the next day. Thus, the day where the changes occur will be analysed for a change in business outlook as compared with the rating a day before, and will be defined as time t. The majority of the tests in this study is focused on the day following the change in business outlook, defined as t+1. In this study, I have made use of companies' closing prices to calculate returns. The returns on day t, would for example be calculated by deducting and dividing it with the closing price at time t-1.

[5] https://connect.data.com/directory/company/fortune/1000

Figure 2: *Number of BOA Observations Per Day of the Week.*



The business outlook measure adjusts as soon as an employee answers to a simple input-figure, that asks the employee their thoughts regarding the company's next 6 Month' Business Outlook. The available responses include "Positive", "No Opinion" and "Negative". Based on these responses, the business outlook rating of a company gets adjusted. See appendix Figure A1 for a screenshot of the input box.

Similar to consumers having web sites where they can share their experiences relating to products and services, employees also have websites to express their opinion about jobs and companies, widely known as employer review web sites. Although there are not yet any studies that make use of a real-time business outlook rating, I base my research on it because it is particularly useful in identifying the relationship business outlook and returns.

Glassdoor is an employer review site where workers validate their companies and positions, by freely and anonymously providing their overall perceptions on various factors. In order to understand the importance and penetration of the website, we made use of Alexa to measure the site popularity. As of May 2016, the results show Glassdoor being by far the best employer review site and its importance far outstretch that of StockTwist, Seeking Alpha, Motley Fool and other financial social media niche sites[6].

The firms included in our study belong to a total of 49 different business sectors according to the classification used by Glassdoor. The number of BOA are 3502 and the average number of BOAs per company over the sample period amounted to 5.3. Also, from Figure 2, the ratings are somewhat clustered to the middle of the week. It is good to know that the data is not clustered on Monday or Friday, as other effects might explain returns on those days. What makes this data especially useful is the large number of ratings gathered. A possible point of criticism is the fact that the data was downloaded from essentially a social media site and that companies may manipulate their reviews by proactively encouraging employees who are fond of the company to give their rating. However, after doing a frequency analysis, this does not seem to be the case, adjustments for improving and decreasing outlook has similar time deviations, meaning that improving outlook adjustments is not as a result of one HR manager creating multiple profiles after which they up vote the company multiple times in a short period of time.

The key advantage of using the Glassdoor dataset is that it is voluntarily supplied by employees behind the veil of anonymity; as such it truly captures internal stakeholders' perceptions in the eyes of the beholder. There are various aspects that can give us comfort over the accuracy of the content and assessments. Every employee can only post one review of the company, decreasing the ability to systematically distort the information or opinion of other reviewers. Glassdoor then screens and maintains the integrity of the posted reviews.

Because Glassdoor reviews are posted in real time, it is possible to engage in a higher frequency study of forecasted business outlook, compared to outlook and earnings expectations that happen at most on a quarterly basis per survey or annual report. There is an

[6] http://www.alexa.com/siteinfo/glassdoor.com

implicit assumption that voluntary disclosure mechanism fails to produce quality information regarding firms. Forecasts of future earnings are for example provided for by corporate managements and might not be very informative.

Most studies ignore the silent voices of employees who are arguably the best information source of what is happening 'on the ground'. In this study I will make use of CAPM to analyse the performance of my portfolios. The dependent variable is the excess return on day *t* for each portfolio, *p*. The risk free rate is the 13-week treasury. B_p is the regressed beta for the portfolio. To calculate the beta, I regressed it on the S&P 500 for 120 days ending before the start of the sample. Market return (R_m) is proxied by the S&P 500 return. And ε_p is the residuals.

4 Research Design:

4.1 Portfolio Construction

I construct calendar time portfolios to identify the returns obtainable from adjustments in business outlook. My initial portfolio design proceeds as follows. For each trading day (t) in the sample period, I identify all stocks that have experienced a change in business outlook, defined on page 24. The stocks then get partitioned into portfolios for an upward and downward change. Below is an indication of the different portfolios used in this study:

$$P\left\{P_{up}, P_{down}, P_{up\_large}, P_{down\_large}, P_{up\_small}, P_{down\_small}\right\}$$

Where,

P_{up} = Portfolio that consists of all the firms that experienced an upward BOA at time

P_{down} = Portfolio that consists of all the firms that experienced a downward BOA at t.

P_{up_large} = Similar to P_{up}, but for the top half of firms in terms of Market Equity.

P_{down_large} = Similar to P_{down}, but for the top half of firms in terms of Market Equity.

P_{up_small} = Similar to P_{up}, but for the bottom half of firms in terms of Market Equity.

P_{down_small} = Similar to P_{down}, but for the bottom half of firms in terms of Market

After determining the composition of each portfolio *P* as of the close of trading on date *t-1*, the value-weighted return for date *t* is calculated. Denoted by R_{pt} for portfolio *P*, this return is given by:

$$R_{pt} = \sum_{i=1}^{n_{pt-1}} x_{it-1} R_{it} \tag{1}$$

Where,

x_{it-1} = The market value of firm *i* as of the close of the trading day on date *t-1* divided by the aggregate market capitalisation of all firms in portfolio *P* as of the close of the trading day.

R_{it} = The return on the common stock of firm *i* on date *t*.

n_{pt-1} = The number of firms in portfolio *P* at the close of the trading on date *t-1*

There are a few reasons why I start off with using value weighted instead of equal weighted portfolios. First, it is expected that equal weighting daily returns would lead to overstated portfolio returns. Value weighting would allow me to better capture the economic significance of the results, the reason being that the larger more important firms will be more heavily represented in the aggregate return than will those in the smaller firms. Markets are also likely to be more efficient for the largest securities. I have, however also included equal weighting for robustness see in Equation 2 below.

$$R_{pt} = \frac{1}{n}\sum_{i=1}^{n_{pt-1}} R_{it} \tag{2}$$

Once the respective portfolios have been calculated for each of the trading days, I used a simple formula to investigate the effect on returns when I use longer holding periods. Due to the small amount of trading days, I have decided to incorporate and overlapping strategy. I am able to do this due to the fact that the average time deviation of BOAs per firm is around 10 days, so there will not be a lot of overlapping returns to bias the results.

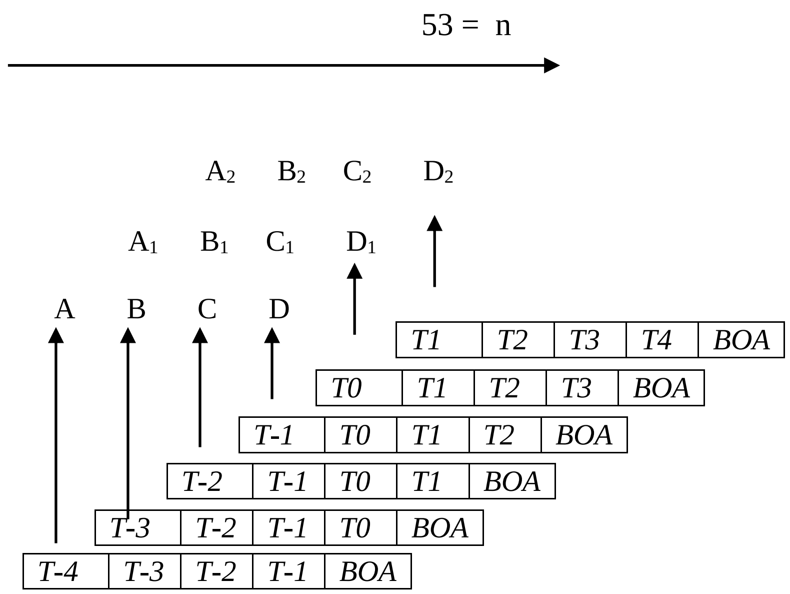
$$R_{P\ t-n,\ t-1} = \frac{1}{n}\sum_{i=1}^{n_{pt-1}} R_{pt} \tag{3}$$

Equation 3 is the calculation required for constructing a composite portfolio. I follow a methodology as presented in Jegadeesh and Titman (2001) for momentum strategies with a few adjustments to the model such as also including portfolio formation before an adjustment in business outlook. I also use daily data instead of monthly data. In my model, n-1 is the holding period. At the end of each day, the oldest sub-portfolio, formed at the end of t-n, is dropped from the composite formula and its position is taken by a new sub-portfolio that is formed based on the BOAs of the following day. Due to the short timescales used, the longest being 19 days, I have chosen to use an arithmetic average of the respective sub-portfolios. I have constructed overlapping portfolio rebalancing with longer holding periods for both equal (Equation 1) and value weighted (Equation 2). Below is an indication of some of the rebalancing durations tested.

$$T\,\{(-20,-1),(-10,-1),(-7,-1),(-4,-1),-1,0,1,(1,4),(1,7),(1,10),(1,20)\}$$

Example of Overlapping Rebalancing Methodology - Before BOA:

This section illustrates the process with an example, using (*t*-4, *t*-1). Here, *t* is the point where the BOAs take place. The first term, *t*-4, refers to the portfolio formation start and *t*-1 the portfolio end relative to the BOAs. A portfolio is formed on day t-4 based on an adjustment on day t using value weighting (equation 1) or equal weighting (equation 3). The portfolio stretches from *t*-4 to *t*-1. In this strategy, I don't take the returns on the day, *t*, into account as I want to isolate pre-event returns. The absolute value of the first term minus one, |-4| - 1= 3, is the holding period. After every iteration to calculate the composite return, the whole operation moves a day ahead and the old sub-sample, in our case *t*-4, gets dropped in favour for a new one. Therefore, we have (*t*-3, *t*0) based on the BOAs that occurred at day *t*+1. Lastly, the daily arithmetic average of sub portfolio returns for every observation day, n, is calculated using the Equation 3, after which it feeds into the performance evaluation model, Equation 5.



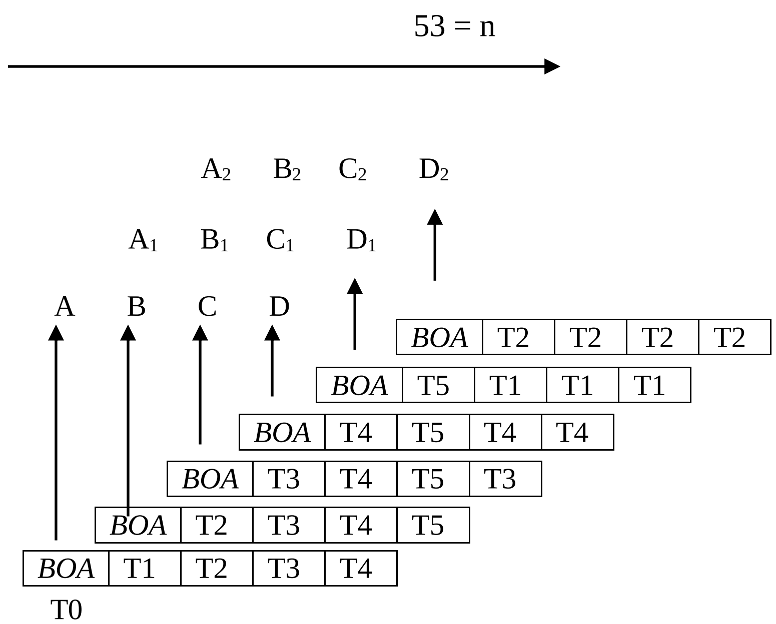
$X_n \{A_n, B_n, C_n, D_n\}$

$X_n, = (R (T_n\text{-}4) + R (T_n\text{-}3) + R (T_n\text{-}2) + R (T_n\text{-}1))/4)$ (Equation 2)

$RP_n = (A_n + B_n + C_n + D_n)/4$ (Equation 3)

Example of Overlapping Rebalancing Methodology - After BOA:

This is similar to the example above, apart from calculating returns after a change in business outlook (BOA) instead of before . In this visual example (t+1, t+4) is used. Compare the examples and notice the position of the BOA shifts. Here, the first change in business outlook is positioned at t 0.



X_n {A_n, B_n, C_n, D_n}

X_n, = (R (T_n+1) + R (T_n+2) + R (T_n+3) + R (T_n+4))/4) (Equation 2)

$RP_n = (A_n + B_n + C_n + D_n)/4$ (Equation 3)

I have furthermore studied the effects of early reactions by forming daily hypothetical portfolios before a change in BOA and moreover accounted for delayed reaction by looking at later portfolio formation. I used daily rebalancing and tested the days relative to the BOA as outlined below.

$$T\{-4, -3, -2, -1, 0, 1, 2, 3, 4\}$$

In this study I also look into the cumulative effects of raw portfolio returns and compare it against the market in a diagram. To calculate the cumulative return over the sample period, I used the following equation. The daily return R_{pt} are compounded over *n* trading days of the sample to yield to total cumulative return of R_{p}t.

$$R_{p\mathrm{t}} = \prod_{t=1}^{n}(1 + R_{pt}) - 1 \tag{4}$$

An example of a portfolio's formation follows, below I illustrate the logic of how a value weighted portfolio that experiences an upwards BOA gets formed, where $BizUp_{it}$ is a binomial variable that equals true when firm *i* experienced an upwards BOA at time *t*.

$$R_{Pupt} = \sum_{i=1}^{n_{pt-1}} x_{it-1}R_{it},\ i = n \rightarrow BizUp_{it} = True$$

4.2 Performance Evaluation

In this study I want to determine whether profitable investment strategies exist with respect to BOAs, I begin by determining the risk adjusted returns using the Capital Asset Pricing Model. I estimate the following daily time series regression, This test yields parameter estimates of α_p and β_p:

$$R_{pt} - R_{ft} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + \epsilon_{pt} \tag{5}$$

Where,

R_{ft} = The daily return t on the 13-week treasury bills.

α_p = The estimated CAPM intercept (Jensen's alpha)

β_p = The estimated market beta, and

ϵ_{pt} = The regression error term

R_{mt} = The daily return t of the S&P 500 value weighted index

I also employ the CAPM model to visually chart the abnormal portfolio returns 8 days around the BOA event date from t-4 to t+4, see figure 4. All the above mentioned analyses are the best methodologies to test the hypothesis, as to whether buying improving firms lead to significant abnormal returns and whether shorting worsening firms lead to significant abnormal returns after changes in business outlook.

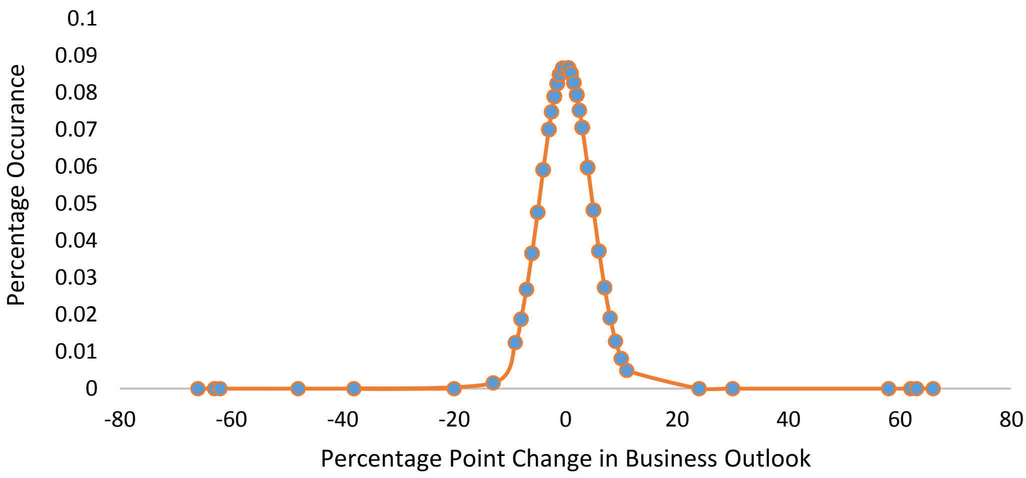
4.3 Business Outlook

To determine whether investors can profit from business outlook adjustments (BOAs), I first have to discuss how BOAs are defined in this study. I use the employee business outlook data as a proxy for the overall business outlook of a firm. In analysing the business outlook dataset, I have identified the mean absolute change in outlook to be around 1.8 %. I have, thus, focused on incorporating all absolute changes of 1 percentage point (pp) and higher into the study to ensure the comprehensive nature of the analysis. By doing this I can be assured that I am not favouring small companies over large ones. The average adjustment for a small firm is 2% and a large firm is 1.6%. Only 403 large firms experience greater than 1 pp adjustments, whereas the bottom median experienced 600 and more adjustments above 1 pp. Therefore, the vast majority of changes do not exceed 1 pp.

As a result of using defining the 1pp threshold, large firms experienced 1782 adjustments overall and small firms experienced 1557 adjustments. See figure 1 for a breakdown of upwards and downward adjustments. The overall mean percentage point change in business outlook over the sample period is 0.023%, this can be a preliminary indication that firms and the overall stock market experienced growth over this period.

Following the upper fence and lower fence strategy, calculated by using the first/third quartile plus the IQR multiplied one and a half time, I have identified 21 outliers (0.6%) in my business outlook adjustment dataset. These outliers are not a big issue as a result of the way in which I conduct this study by giving equal weight to each adjustment non-withstanding its magnitude. The outliers are also mostly small firms and I also perform tests with just large firms so it will be satisfactory to examine those isolated results.

Figure 3*: Distribution of Business Outlook Percentage Point Adjustments*



To ensure that the change in business outlook does not occur as a result of earnings announcement noise, I have followed a similar strategy to Loh and Stulz (2011) and excluded business outlook adjustment that fall in the three-day window (-1, 1) around earnings announcements (8 observations excluded). Lastly, for the purpose of this study I have ignored the occurrence of neutral employee ratings because they do not lead to any adjustments. I have included Figure 3 to illustrate the distribution of the BOA dataset. Also, see Figure A1 for the employee inputs necessary for the creation of this dataset.

5 Empirical Results

5.1 Descriptive Statistics

The summary statistics of key variables used for the main regressions in this study are presented in table A3 in the appendix. This table looks at both improving and worsening value-weighted firm portfolio measures, three days around the BOA. This table splits the measures into improving and worsening firm portfolios. For the improving portfolio, formed one day after the adjustment, denoted as $P_{(1,1)}$, the excess return (ri_rf) is defined as the portfolio return adjusted by the risk-free rate and it averaged a negative daily return of 0.016 %. For the worsening portfolio, P1, on the right-hand side of the table, the excess return equals a negative daily value of 0.109% Although the improving portfolio's excess return is negative, it is approximately 7 times smaller in magnitude than that of the worsening portfolio.

The above averages are very interesting given that there are no significant differences between the size of the firms, nor the book-to-market value, hence these characteristics can't explain the differences. The improving portfolio has an average size (market equity) of 59,332 ($MM) and the worsening portfolio has an average size of 56,188 ($MM). The improving portfolio has a book-to-market value of 0.378 and the worsening portfolio has a book-to-market of 0.366.

In table A3, I have also included difference in mean tests. The results are quite interesting, but they only show significance at the 10% level for items such as the difference in raw returns and risk adjusted returns between improving and worsening firms, and only for the day before a BOA. For the purpose of this study, I have decided to constrain statistical significance to the 5% level and to perform a two sided t-test to preserve the validity of the study due the possibility of noise. I have also added the descriptive statistics for equal weighted portfolios in Table A4 of which I replicate what I have done for A3 as described above.

In table A4, I present the first set of robustness statistics in the form of equally weighted portfolios. The sample statistics for equally weighted portfolios shows significant differences to that of the value weighted portfolios in A3. The average equal weighted portfolio is much smaller in market equity compared to that of the value weighted portfolio and has a higher book-to-market value.

To gain a more holistic understanding of these portfolios, I have incorporated an extensive map of the summary statistics of the worsening and improving portfolios in Table

A5. These tables show that it is possible that the worsening portfolios have some outliers, the 1st percentile for excess return of P1 is lower than the market, the same applies for the improving portfolio at the 99th percentile. The skewness and kurtosis are, however quite similar for both the portfolios.

Table 1 reports the long-short portfolios of worsening and improving business outlook. Table 2 reports on some important portfolio characteristics that can affect the validity of the results obtained in Table 1. Table 3 presents an extrapolated estimate of raw portfolio returns for all firms and a subsample of large firms. Table 4 shows the result of risk adjusted value-weighted returns using CAPM. Table 5 replicates Table 4 for equal-weighted robustness regressions. Table 6 identify the average daily abnormal returns surrounding BOAs. Table 7 replicates Table 4, for a subsamples of large and small firms. Table 8 presents 5 robustness tests performed on the benchmark portfolio. Table A7 and A8 in the Appendix reports portfolios with less rebalancing for days before and after the business outlook adjustment using an overlapping rebalancing strategy. A9 and A10 also in the Appendix, report the same information, but for a subsample of large firms.

5.2 Raw Returns

I classified my data into two parts, namely positive changes and negative changes in business outlook. In this study, I attempt to identify whether investors react to changes in business outlook in a timely fashion, to ascertain the importance of real-time business outlook adjustments. Significant subsequent returns can be indicative of the importance of and information quality of employees' knowledge of the firm. An adjustment might also be informative for investors due to the important role employee morale and satisfaction play in determining firms' long-run stock returns (Edmans, 2012).

To do this study, I will execute a benchmark portfolio strategy, $P_{(1,1)}$, where day 0 is classified as the day a Business Outlook Adjustment (BOA) occurs. If a stock's business outlook is downgraded on day 0, it is sold short at the closing price on day 1 and the short position is closed at the closing price on day 2. A similar process follows for the long portfolio of firms where the business outlook is upgraded. This process is done for each of the 56 consecutive trading days.

In Table 1 Panel A, I identify long-short portfolios for a full sample of firms, longing improving portfolios and shorting worsening portfolios. In panel B, I identify a subsample of the top median firms in terms of market equity (large firms). In this table I have also included a hypothetical portfolio to identify the returns that could be earned the day before a change in business outlook, $P_{(-1,1)}$, to identify whether insiders trade on this knowledge or whether an event occurred after which a momentum effect or slow shareholder response could explain subsequent profits. It can however be argued that if it was a momentum effect, then it would persist on the day of the adjustment, but it does not, as would later be seen in Figure 7.

Panel A, the full sample of firms, shows positive non-significant profits, for both value and equal weighted portfolios, the day before and the day after a change in business outlook. However, value-weighted portfolios seem to outperform equal-weighted portfolios. After identifying the size characteristics, it is noted that the average value-weighted portfolio firm is almost twice the size of equal-weighted portfolio firms. For that reason, I decided to look at a large subsample of firms to see how the portfolio profits change.

For the large firms in Panel A, the size and b/m values are nearly identical for improving and worsening firms as can be seen in Table 2. It would therefore be ideal to investigate whether a long-short portfolio of large firms will provide significant returns. At a later stage we also adjust for market risk to see if other risks can explain the long-short portfolio returns (See Appendix Table A3 and A4). In Table 1, Panel B, I have added the test for large firm portfolios, here we do indeed see significant profits. For the benchmark portfolio, $P_{(1,1)}$, the majority of the profits are driven by the short-leg of worsening firms. The opposite is true for the hypothetical portfolio, formed a day before the adjustment in business outlook, where the returns are mostly driven by the long-leg of improving firms.

Table 1: *Shorting Worsening Firms and Buying Improving Firms*

	Value Weighted			Equal Weighted		
	Improv-ing	Worsen-ing	Long-Short	Improv-ing	Worsen-ing	Long-Short
	mean	mean	Difference pp.	mean	Mean	Difference pp.
Panel A: Full Sample						
$P_{(-1,1)}$						
Raw Returns	0.00184	0.00066	0.002495	0.00220	-0.000682	0.001518
t-stat	(1.8759)	(0.3921)	(1.7649)	(1.7553)	(-0.4116)	(1.2284)
$P_{(1,1)}$						
Raw Returns	0.00007	0.00086	0.000928	-0.0001	0.00011	0.000016
t-stat	(0.0423)	(0.5202)	(0.8367)	(-0.1423)	(0.0762)	(0.0176)
Panel A: Large Firm Portfolio						
$P_{(-1,1)}$						
Raw Returns	0.0016	0.00144	0.00304	0.00222	0.00086	0.003081
t-stat	(1.5631)	(1.2874)	(2.2929*)	(1.8964)	(0.6972)	(2.2439*)
$P_{(1,1)}$						
Raw Returns	0.00063	0.00339	0.004017	0.00099	0.00314	0.004136
t-stat	(0.6154)	(3.031*)	(2.6244*)	(0.8457)	(2.5458*)	(2.8678*)

=* p<0.05 ** p<0.01 *** p<0.001

This table reports the daily equal and value-weighted long-short portfolio regressions, by longing the improving firms and shorting the worsening firms of both the full sample and the large subsample. This table reports the raw returns a day before the BOA ($P_{(-1,1)}$) as well as the benchmark portfolio to calculate the raw returns the day after the BOA ($P_{(1,1)}$). Both $P_{(-1,1)}$ and $P_{(1,1)}$ is rebalanced on a daily basis. Statistical significance is based on a pairs t-stat. The results above are raw and not adjusted for risks. Table A3 and A4 also show the differences in means and pairs t-stat adjusted for risk using CAPM. The results and significance remained mostly unchanged except some improvements in magnitude.

This can be indicative of positive news reaching the market before an upwards adjustment in business outlook. Similarly, management might be slower to release negative news, hence the strong negative reaction after a downwards BOA. A similar effect has been presented by

Kothari et al. (2009), who shows that managers defer the dissemination of bad news and accelerate the revelation of good news. Other than the portfolio formations reported in this table, I have also looked at further long-short portfolios 8 days around the BOA, none of which show any significant profits. Moreover, I have controlled for earnings announcements and have excluded conflicting observations.

Table 2: *Portfolio Characteristics*

	Value Weighted			Equal Weighted		
	Improv-ing	Worsen-ing		Improv-ing	Worsen-ing	
	mean	mean	Difference	mean	mean	Difference
Panel A: Full Sample - $P_{(1,1)}$						
Size [ME]	59,332	56,188	3144	24,082	25,641	-1578
			(0.4892)			(-0.5554)
B/M	0.378	0.366	0.01200	0.423	0.438	-0.015
			(0.3104)			(-0.4142)
Panel A: Large Firm Portfolio - $P_{(1,1)}$						
Size [ME]	107,664	111,886	-4222	43,521	42,054	1467
			(-0.2366)			(0.2545)
B/M	0.347	0.351	-0.004	0.373	0.377	-0.004
			(-0.0559)			(-0.0662)

=* p<0.05 ** p<0.01 *** p<0.001

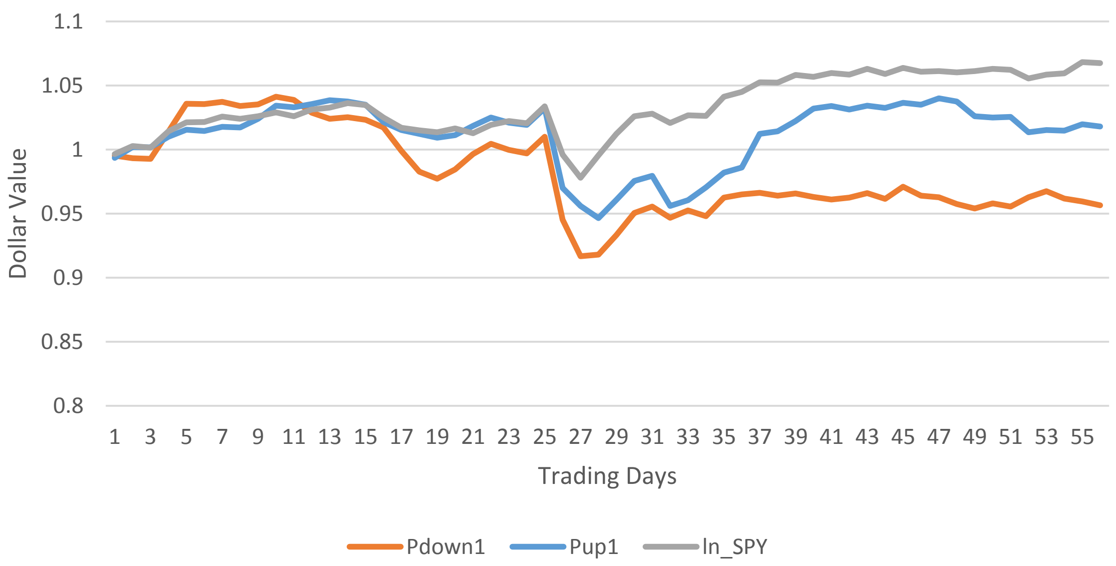
This table reports the daily equal and value weighted market equity and book-to-market figures for improving and worsening, full sample (Panel A) and large subsample (Panel B) benchmark portfolios formed a day after the BOAs and held for a day, $P_{(1,1)}$, as reported in Table 1. The results indicate strong similarities in characteristics between worsening and improving firms. Hence, if these characteristics are perfect proxies for risk it makes long-short portfolios all the more viable. In Table 4 and 7, I also adjust these portfolios for market risk, using the Capital Asset Pricing Model.

Table 2 reports the Size and Book-to-Market characteristics of the worsening and improving benchmark portfolios for a full sample and a large subsample of portfolio firms. At a later stage we will also calculate the risk-adjusted return using the CAPM. The reason this study does not use FF4 is because these factors are only reported up and till June 2016 and my sample period stretches beyond that date.

5.3 Portfolio Valuation

From the tests performed thus far, three results and possible explanations stick out. First as a result of either, insider trades, early information leakage or other public disclosures the stock price adjusts the day before the BOA, mostly affect improving-firm portfolio return. Second, due to the public disclosure of outlook adjustments, more investors catch hold of the worsening business outlook of firms, which creates more downward pressure on the stock on the subsequent trading day. Third, large firms outperform a full sample and a subsample of small firms. This can be due to BOAs being more trustworthy coming from large firms or due to it being easier to short-sell large firms compared to smaller firms. Over this period the general market (S&P 500) experienced significant gains, this therefore creates a case for looking at the value of benchmark portfolios and comparing it to the general market over the sample period.

Figure 4: *Portfolio Value, Buying and Holding Upward and Downward Changing Portfolios with Daily Rebalancing - $P_{(1,1)}$.*



Pdown1 shows the *buy* and hold value weighted portfolio of worsening firms rebalanced daily, $P_{(1,1)}$, starting the day after the BOA. *Pup1* is similar to *Pdown1*, but for improving firms. The S&P 500 market return is presented as *ln_SPY*. This illustrates a loss in value by going long on the worsening portfolio. When worsening portfolio of firm get shorted using the benchmark strategy you can gain 4% in value (See Table 3).

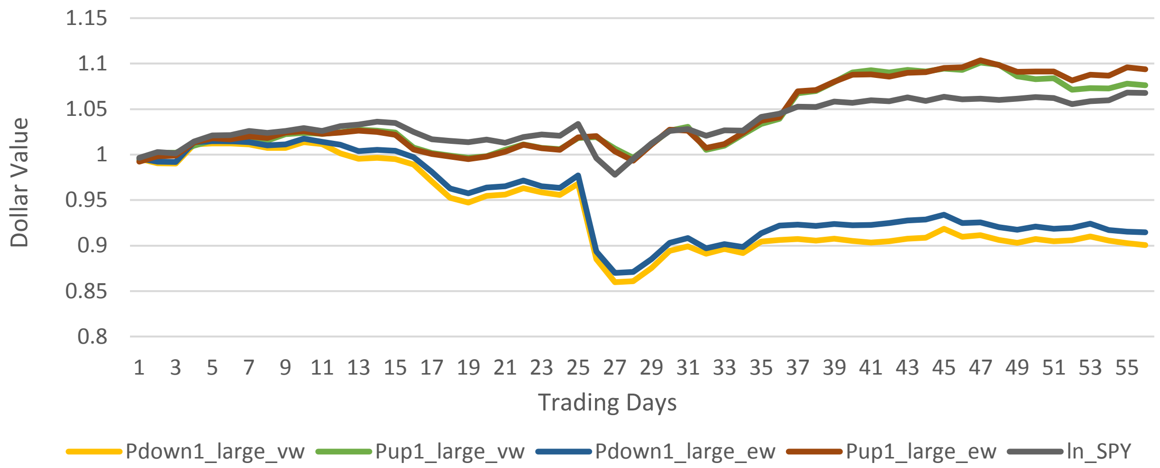
Figure 4 plots the change in value of buying improving and worsening value weighted portfolios. Here I present the long portfolio value case for both improving and worsening portfolios as it better illustrates the disparity between the two and visually demonstrates how it can be profitable to short-sell a portfolio of worsening firms the day after the BOA with daily rebalancing. The improving portfolio seems to be outpaced by the general market. A decrease in the market also seems to have a smaller impact on Pup_1 than $Pdown_1$ and the converse is also true for an increase in the general market.

Larger firms' have more observations as shown in Figure 1, they also have more changes above the 1 percentage point (pp) threshold and it is conceivable that a large pp change produces better results. Glassdoor data might be a bit noisy for smaller firms, which can explain why we only see strong results for a large subsample. Large firms are also known to be more informationally efficient, so we would expect large firms to react more timely to new news signalled by an employee's perception of a change in business outlook. It is also easier to find a market to short-sell large firms compared to smaller firms so we would expect to see slower adjustments by small firms and faster adjustments by large firms.

Figure 5 replicates Figure 4, but for large firms and presents both value and equal weighted portfolios. It depicts the same general results as obtained in Table 1. Improving portfolios are slightly more profitable than the market and worsening portfolios significantly underperform which means that it offers a great long-short portfolio opportunity. Figure 5 shows that a subsample of large firms produces a much higher benchmark portfolio value than that of the full sample. I have incorporated both equal-weighted and value-weighted returns on the sized portfolios and show that these different methods of weighting produce the same results.

Table 3 reports the accumulated raw sample returns and the expected annual returns as extrapolated from the compounded average obtained over 56 consecutive trading days. It shows that large portfolios significantly outperform portfolios constructed from the full sample and that profitable long-short (L-S) opportunities exist.

***Figure 5:** Portfolio value, buying and holding upward and downward changing portfolios of large firms with daily rebalancing over the sample period.*



$Pdown_1$_large_vw shows how buying and holding a worsening, value weighted portfolio of large firms significantly decrease in value, in other words shorting this portfolio will lead to value gains. Pup_1_large_vw presents the value of an improving, value-weighted portfolio of large firms. $Pdown_1$_large_ew is a worsening, equal weighted portfolio of large firms. Pup_1_large_ew is the improving, equal-weighted portfolio of large firms. The S&P market return is presented as *ln_SPY.*

***Table 3:** Annualised accumulated raw portfolio returns for the upward and downward changing portfolios with daily rebalancing, extrapolated to 252 trading days.*

Accumulated Returns	Large Sub-Sample			Full Sample			
	Pdown	Pup	L-S	Pdown	Pup	L-S	ln_SPY
Panel A: Accumulated Sample Period Returns							
Value Weighted	10%	7%	17%	4%	2%	6%	7%
Equal Weighted	9%	9%	18%	0.5%	0.6%	1%	n/a
Panel B: Accumulated Annualised Returns							
Value Weighted	38%	40%	78%	18%	9%	27%	35%
Equal Weighted	33%	51%	84%	2%	2%	4%	n/a

Pdown/Pup is the accumulated raw portfolio return of shorting/buying worsening/improving firm portfolios rebalanced daily, starting the day after the BOA and keeping the position for a day, before closing it out (i.e. the benchmark portfolio strategy). Panel A presents the accumulated returns over the sample period. Panel B follows from the calculation of compounding the daily geometric average return, as calculated from 56 sample days, for 252 consecutive trading days. The S&P 500 market return is presented as *ln_SPY*. L-S refers to the various long short investment opportunity.

5.4 *Risk-Adjusted Returns*

Table 4 presents the value-weighted abnormal returns that can be achieved using Equation 5, which calculates the risk adjusted returns using the Capital Asset Pricing Model (CAPM). The reason this is done, is to make sure that the raw returns in the previous section is not driven by the portfolios' sensitivity to the overall market. As per this study's hypothesis we want to see whether investors can profit from a strategy by short-selling worsening firms and/or buying improving firms. And as discussed, we do this by forming portfolios one day after a change in business outlook with daily rebalancing ($P_{(1,1)}$). Table 4 presents the regression of portfolios from a full sample of improving and worsening firms.

Table 4: *OLS Regressions of Daily Portfolio Value-Weighted Returns for Six Portfolios That Tracks Positive and Negative Adjustments of Outlook a Day Before, On the Day, and a Day After Firm Outlook Adjustments Takes Place.*

	Improving			Worsening		
	(1)	(2) (BOA)	(3)	(4)	(5) (BOA)	(6)
	$Pup_{(-1,1)}$	$Pup_{(0,1)}$	$Pup_{(1,1)}$	$Pdown_{(-1,1)}$	$Pdown_{(0,1)}$	$Pdown_{(1,1)}$
Beta	0.494***	0.860***	1.113***	0.704***	1.040***	1.257***
	(4.85)	(8.93)	(9.19)	(3.82)	(10.79)	(11.22)
Alpha	0.00119	-0.00008	-0.00125	0.00149	-0.00103	0.00232*
	(1.42)	(-0.10)	(-1.25)	(0.99)	(-1.31)	(2.52)
N	56	56	56	56	56	56
R-sq	0.307	0.596	0.610	0.216	0.683	0.700

t-statistics in parenthesis

* p<0.05 ** p<0.01 *** p<0.001

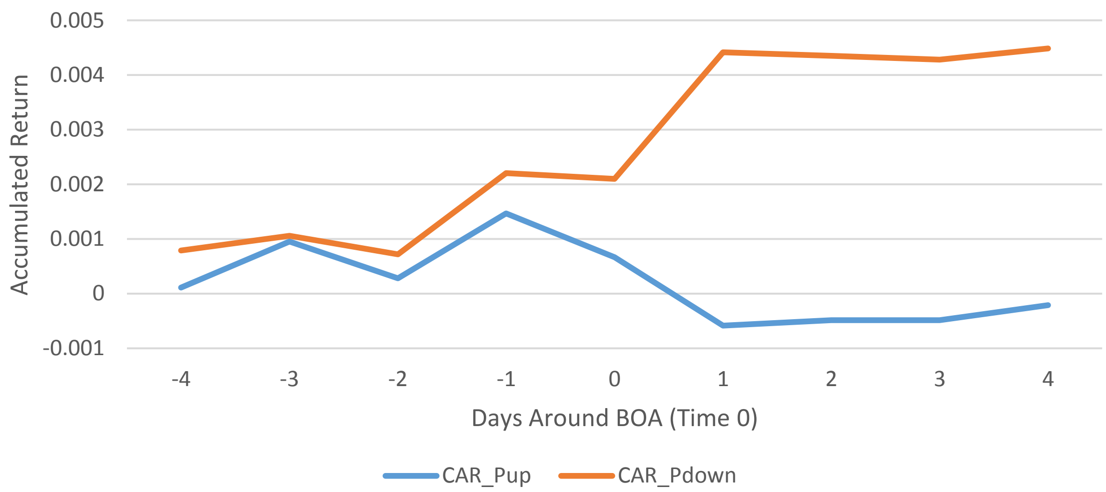
This table reports the average abnormal value-weigted returns corresponding to an upward and downward adjustment in business outlook. Statistical significance is based on a t-stat. The dependent variable is the respective value-weighted portfolio return adjusted by a risk-free rate. The independent variable is the market risk premium. It is the difference between daily returns on the S&P 500 and the 13-week treasury bond yield as a proxy for the risk free rate. (1) Portfolio $Pup_{(-1,1)}$ is formed from t_{-2} to t_{-1}, t being the date of a positive change in business outlook in firms. (2) Pup is formed from t-1 to t. (3) $Pup_{(1,1)}$ is formed from t_0 to t_{+1}. (4), (5) and (6) replicate the above mentioned portfolios, but this time for firms with worsening outlook adjustments (Pdown).

At first glance, shorting a worsening portfolio of firms produces significant abnormal profit, whereas longing improving firms produce an unexpected negative signed alpha. The worsening portfolio's raw returns as presented in Table 1 has thus increased in significance and size after an adjustment in risk, whereas the increasing portfolio's significance has decreased. It can also be noted that the CAPM coefficient for the worsening portfolio are larger than that of an improving portfolio. Comparable to Jame (2016), who looked at sell side earnings adjustment estimates, the results show that downward business outlook adjustments are more informative than upward adjustments and are also more timely in price reaction as can be seen in Figure 6. To identify whether there is delayed effects I extended the above analysis and graph the daily abnormal returns as adjusted with the CAPM model in Figure 7.

Figure 6 shows that the majority of abnormal returns from short-selling a portfolio of worsening firms, $Pdown_{(1,1)}$, occur the day after the change in business outlook (t_1 to t_2). This is within expectations, which is why the benchmark portfolio is constructed over this period following firms BOAs at t_0. It is also worth noting that there's some abnormal returns leading up to the change in outlook. The improving firm portfolio, Pup, on the other hand, acted against expectations, it experienced respective non-significant increases and decreases before and after the BOA. Table 5 presents the regressions I performed around the BOA; it also presents the daily abnormal return of the portfolios used to construct Figure 7. I used Equation 1, utilising value weighting to calculate the portfolio returns on each day.

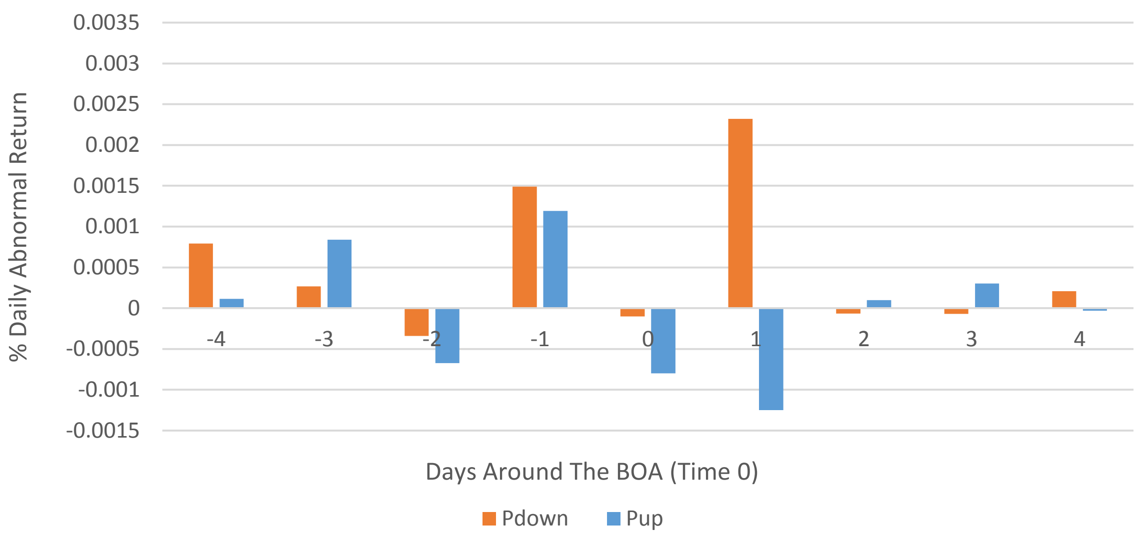
This is an interesting phenomena in that downward BOAs seem to cause a strong reaction, whereas upward adjustments in business outlook does not. It is possible that the upward adjustments in business outlook is spuriously entered by the firms' HR or PR representatives to improve their public image. This might explain why the benchmark portfolio for upward adjustments lead to negative returns. This is more extensively discussed under the limitations section.

***Figure 6**: Accumulated Abnormal Return, 8-Days Around the BOA.*



CAR_Pup is the 8-days improving-firm accumulated portfolio return of which time 0 is the event (*BOA*). *CAR_Pdown* is the worsening-firm accumulated portfolio return. See Figure 7, below, for a complementary representation of the daily abnormal returns.

***Figure 7:** Daily Abnormal Portfolio Returns, 8 Days Around BOA (Time 0)*



Figures A2 are representative of the daily abnormal returns earned 8 days around the BOA. They are supplementary to the cumulative abnormal returns as presented by Figure 4. The regressions feeding into these charts can be seen in appendix Table A12.

Table 5 presents the risk-adjusted returns for equal-weighted portfolios. Similar to the raw returns in Table 1, equal-weighted portfolios underperform value-weighted portfolios for the shorted benchmark portfolio, $\mathrm{Pdown}_{(1,1)}$. Given this difference, I would expect larger stocks to produce better shorting-selling opportunities for worsening portfolio returns one day after a change in business outlook. Furthermore, Table 5's abnormal returns increase in magnitude compared to the raw returns in Table 1.

Table 5: *OLS Regressions of Daily Portfolio Equal-Weighted Returns for Six Portfolios That Tracks Positive and Negative Adjustments of Outlook a Day Before, On the Day, and a Day After Firm Outlook Adjustments Takes Place.*

	Improving			Worsening		
	(1)	(2) (BOA)	(3)	(4)	(5) (BOA)	(6)
	$Pup_{(-1,1)}$	$Pup_{(0,1)}$	$Pup_{(1,1)}$	$Pdown_{(-1,1)}$	$Pdown_{(0,1)}$	$Pdown_{(1,1)}$
Beta	0.660***	1.079***	1.113***	0.762***	1.073***	1.086***
	(5.18)	(12.38)	(10.94)	(4.29)	(10.21)	(10.81)
Alpha	0.00140	0.00099	-0.00135	0.00020	0.00113	0.00140
	(1.34)	(1.38)	(-1.62)	(0.14)	(1.32)	(1.69)
N	55	56	56	55	56	56
R-sq	0.336	0.739	0.689	0.258	0.659	0.684

t statistics in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

This table reports the average equal-weighted abnormal returns corresponding to an upward and downward adjustment in business outlook. Statistical significance is based on a t-stat. The dependent variable is the respective portfolio return adjusted by a risk-free rate. The independent variable is the market risk premium. It is the difference between daily returns on the S&P 500 and the 13-week treasury bond yield as a proxy for the risk free rate. (1) Portfolio $Pup_{(-1)}$ is formed from *t-2* to *t-1, t* being the date of a positive change in business outlook in firms. (2) Pup is formed from *t-1* to *t.* (3) Pup_1 is formed from *t* to *t+1.* (4), (5) and (6) replicate the above mentioned portfolios but this time for firms with worsening outlook adjustments, Pdown.

Table 7 shows the results obtained by splitting our sample in two medians according to market equity. This is a particular useful exercise as it allows us to identify whether the portfolio can be further improved and it allows to understand what effect size has on portfolio performance. Table 7 shows that short-selling large worsening portfolios produces larger returns with a daily alpha of 0.00339, whereas short selling small worsening portfolios does not yield any significant returns. These results effectively match the raw returns in Table 1.

Table 6: *Daily Portfolio Formation, 8 Days Around BOA*

	Panel A: *Worsening Portfolio:* Investigating returns leading up to a change in outlook as well as for a delayed response.								
	$P_{(-4,1)}$	$P_{(-3,1)}$	$P_{(-2,1)}$	$P_{(-1,1)}$	$P_{(0,1)\ (BOA)}$	$P_{(1,1)}$	$P_{(2,1)}$	$P_{(3,1)}$	$P_{(4,1)}$
Beta	0.952***	1.004***	1.089***	0.704***	1.040***	1.257***	1.079***	1.126***	0.962***
	(6.18)	(7.35)	(7.98)	(3.82)	(10.79)	(11.22)	(10.34)	(8.79)	(10.36)
Alpha	0.000791	-0.000276	-0.000342	0.00149	-0.00103	0.00232*	0.0000668	0.0000699	0.000209
	(0.63)	(-0.25)	(-0.31)	0.99)	(-1.31)	(2.52)	(0.08)	(0.07)	(0.28)
N	56	56	56	56	56	56	56	56	56
R-sq	0.410	0.495	0.541	0.216	0.683	0.700	0.664	0.584	0.661

	Panel B: *Improving Portfolio:* Investigating returns leading up to a change in outlook as well as for a delayed response.								
	$P_{(-4,1)}$	$P_{(-3,1)}$	$P_{(-2,1)}$	$P_{(-1,1)}$	$P_{(0,1)}$	$P_{(1,1)}$	$P_{(2,1)}$	$P_{(3,1)}$	$P_{(4,1)}$
Beta	1.047***	1.138***	0.819***	0.494***	0.860***	1.113***	1.147***	1.490***	0.853***
	(8.48)	(15.24)	(8.35)	(4.85)	(8.93)	(9.19)	(10.12)	(4.28)	(7.57)
Alpha	0.000900	0.00106	-0.0000526	0.00119	-0.00008	-0.00125	-0.000529	0.000280	0.000815
	(0.90)	(1.74)	(-0.07)	(1.42)	(-0.10)	(-1.25)	(-0.57)	(0.99)	(0.89)
N	56	56	56	56	56	56	56	56	56
R-sq	0.567	0.809	0.564	0.307	0.596	0.610	0.655	0.249	0.510

="* p<0.05 ** p<0.01 *** p<0.001"

This table presents the daily rebalanced abnormal portfolio returns for firms that experience an outlook adjustment at time t-0. Panel A shows the results for shorting worsening firms for days before and after the BOA; Panel B presents the daily abnormal returns for going long on improving firms. I have provided the returns for 8 days around the BOAs.

Table 7: *OLS Regressions of Daily Value Weighted Portfolio Returns That Tracks Positive and Negative Adjustments of Outlook a Day Before, On the Day, and a Day After the Adjustment Takes Place for a Subsample of Large and Small Firms.*

	Improving			Worsening		
	(1)	(2)	(3)	(4)	(5)	(6)
	$Pup_{(-1,1)}$	$Pup_{(0,1)}$	$Pup_{(1,1)}$	$Pdown_{(-1,1)}$	$Pdown_{(0,1)}$	$Pdown_{(1,1)}$
	Panel A: Large Firms [Top 50 %]					
Beta	0.401***	0.800***	0.46***	0.706***	1.023***	1.477***
	(4.55)	(8.59)	(3.84)	(3.95)	(9.87)	(11.75)
Alpha	0.00160*	-0.000945	0.00063	0.00144	-0.00116	0.00339**
	(2.22)	(-1.25)	(0.64)	(0.99)	(-1.38)	(3.29)
N	56	56	56	56	56	56
R-sq	0.273	0.573	0.214	0.221	0.639	0.719
	Panel B: Small Firms [Bottom 50 %]					
Beta	0.760***	1.225***	1.56***	0.802***	1.219***	1.093***
	(4.46)	(8.50)	(10.87)	(3.66)	(8.36)	(7.69)
Alpha	0.000348	0.000687	-0.00212	-0.00241	-0.000390	0.000724
	(0.25)	(0.59)	(-1.80)	(-1.34)	(-0.33)	(0.62)
N	56	56	56	56	56	56
R-sq	0.266	0.568	0.523	0.198	0.560	0.523

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

This table reports the average value weighted abnormal returns corresponding to an upward and downward adjustment in business outlook. Panel A looks at a subset of large firms, that is the top median of the full sample of firms. Panel B looks at a subset of small firms, that is the lower median of a full sample of firms. Statistical significance is based on a t-stat. The dependent variable is the respective portfolio return adjusted by a risk-free rate. The independent variable is the market risk premium. It is the difference between daily returns of the S&P 500 and the 13-week treasury bond yield as a proxy for the risk free rate. (1) Portfolio $Pup_{(-1)}$ is formed from t_{-2} to t_{-1}, t being the date of a positive change in business outlook in firms. (2) Pup is formed from t-1 to t. (3) Pup_1 is formed from t to t+1. (4), (5) and (6) replicate the above mentioned portfolios but this time by shorting firms with worsening outlook adjustments, (Pdown.

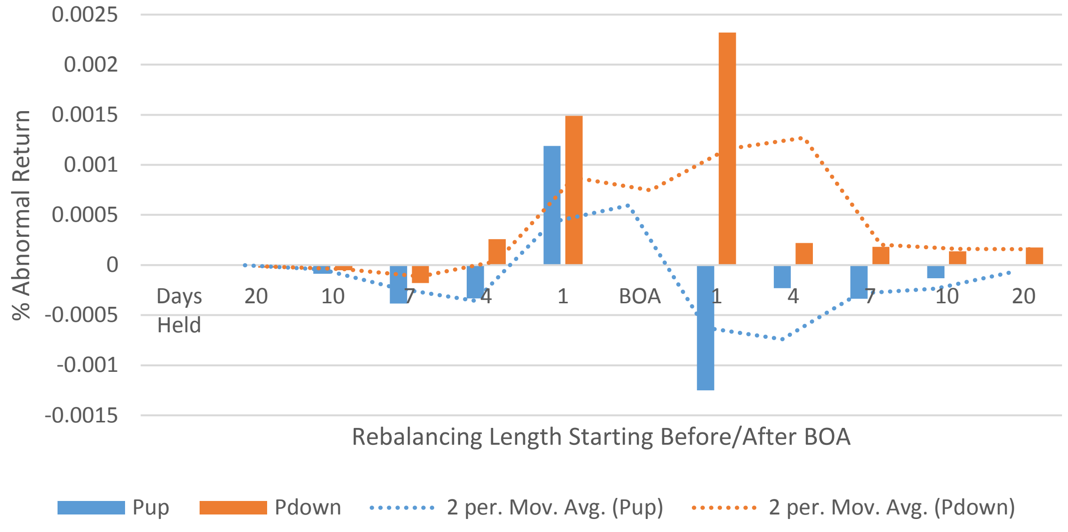
5.5 *Overlapping Rebalancing Strategy*

Figure 8 shows the results obtained by incorporating less rebalancing before and after the BOA and rolling over the sample period, Figure 9 shows the results for a subsample of large firms. And to identify whether smaller firms react slower, we have included Figure 10 for a small sub-sample of firms. I follow an overlapping methodology as presented in Jegadeesh and Titman (2001) with a few adjustments to the model such as using daily data instead of monthly data, see Equation 3 and the example methodology under Research Design. I present the results visually with Figure 8, 9 and 10.

Figure 8, is a symmetrical graphed representation of different lengths of overlapping rebalancing. As an example, "20 days before the BOA" means that the first BOAs investigated is at t+21, the sub portfolio returns is calculated for each day starting at t+1 up and till t+20, i.e. 19 days rebalancing length. The process then moves forward with one day after every iteration. At the next iteration, BOA is at t+22, the t+1subportfolio is dropped and the t+21 sub portfolio is added. This process is repeated until sample end, i.e. 44 times. The various sub portfolio returns are then used to calculate the arithmetic composite return which is regressed to calculate the daily abnormal returns. On the rights hand side, the "20 days after the BOA", follows the same process as above, except now the BOA is at time 0 and the returns are calculated after a changes in business outlook take place. Again for a clear understanding of this process see Equation 3 and its ensuing example.

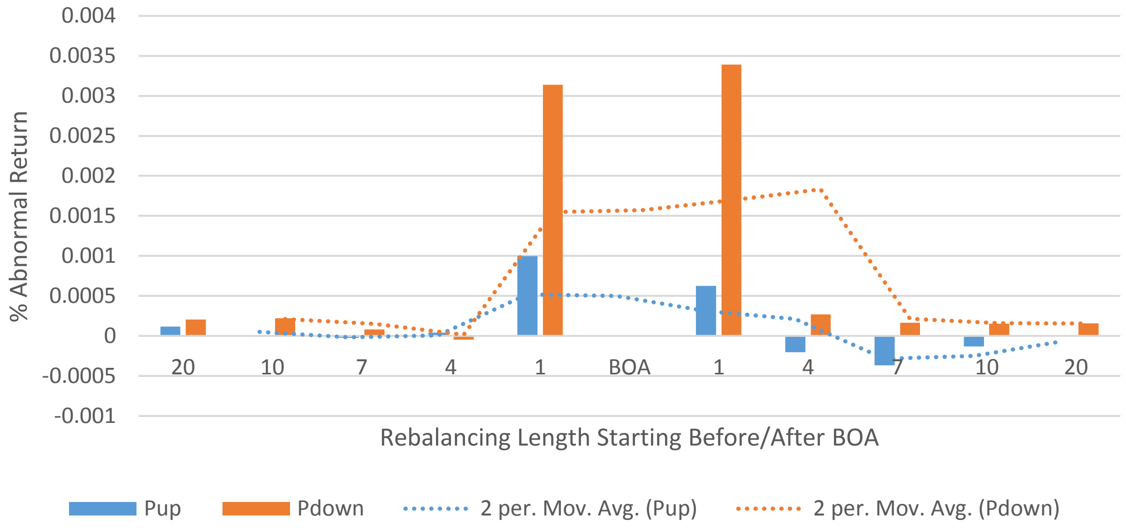
The abnormal returns are computed as daily averages for the composite portfolio. Only daily rebalancing shows significance. The same holds for large firms, as can be seen in Figure 9. For small firms the results are mixed and mostly non-significant, see Figure 10. I have only included value weighted portfolios, however, I have also studied equal weighted portfolios and they also do not show significance for less than daily portfolio rebalancing. For the tests performed, see tables A7 and A8 for Figure 8; see tables A9 and A10 for Figure 9.

Figure 8: *Overlapping Portfolio Strategy: Plotting Abnormal Returns for Holding Periods Before and After BOAs*



The improving portfolios ($Pup_{t-n,\, t-1}$) and worsening portfolios ($Pdown_{\, t-n,\, t-1}$) rebalances at different lengths before and after the BOA. The returns are rolling over the sample period and I use equation 3 to calculate the composite portfolio returns and equation 5 to calculate the abnormal return.

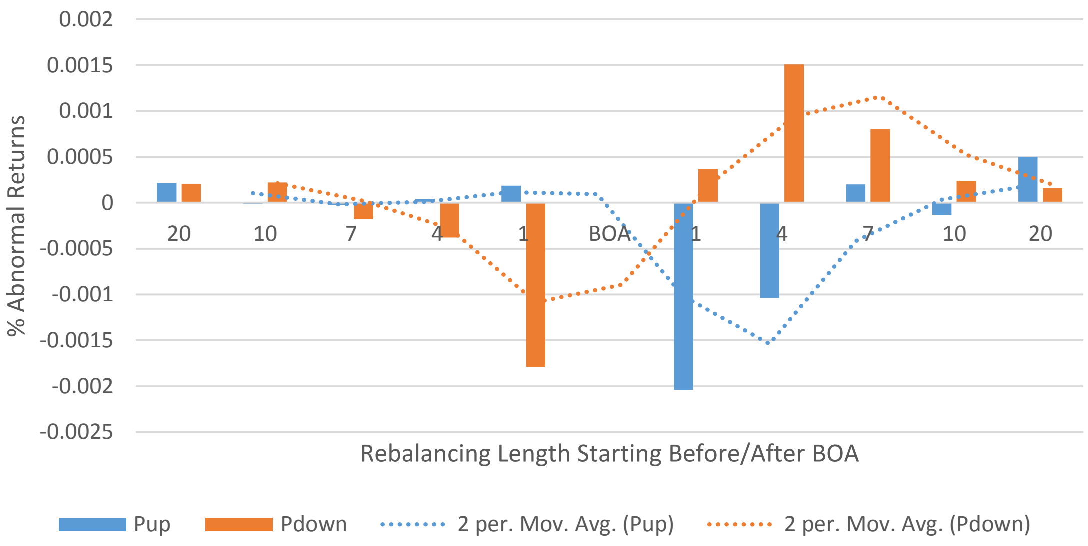
Figure 9: *Overlapping Portfolio Strategy: Plotting Abnormal Returns for Holding Periods Before and After BOAs of Large Firms*



The improving large firm portfolios ($Pup_{t-n,\, t-1}$) and worsening large firm portfolios ($Pdown_{\, t-n,\, t-1}$) rebalances at different lengths before and after the BOA. The returns are rolling over the sample period and I use equation 3 to calculate the composite portfolio returns. Large is defined as the top half of the full sample according to Market Equity

Table 7, Panel B, shows that a portfolio of small firms earns non-significant returns the day after an adjustment, but that the signs are the opposite of what was expected. I have tested the overlapping portfolio strategy using small firms and it showed fairly interesting, but still non-significant results. Figure 10 shows that smaller firms react slower to a downward adjustment in business outlook than large firms and that greater returns can be obtained with 4-day portfolio rebalancing, compared to portfolios formed the day after the adjustment with daily rebalancing. Shorting the former generates 0.15% abnormal return per day, whereas shorting the latter generates only 0.04% abnormal return per day. However, large firms still earn significantly more with daily rebalancing, generating an average of 0.314% abnormal return per day, see Figure 9.

Figure 10: *Overlapping Portfolio Strategy: Plotting Abnormal Returns for Holding Periods Before and After BOAs of Small Firms*



The improving large portfolios ($Pup_{t-n,\, t-1}$) and worsening large portfolios ($Pdown_{t-n,\, t-1}$) rebalances at different lengths before and after the BOA. The returns are rolling over the sample period and I use equation 3 to calculate the composite portfolio returns. Large is defined as the top half of the full sample of firms according to Market Equity.

5.6 Robustness

As seen from most of the tests done, shorting a worsening portfolio formed on the day after a change in business outlook and holding it for one day, produces significantly positive returns. I, however, felt that there are a few factors that could affect the results obtained and have therefore decided to control for those factors by running some robustness tests over the benchmark portfolio ($P_{(1,1)}$) for both improving and worsening firms. In Panel A, I test a full sample of value-weighted portfolio firms (Table 4). In Panel B and C, I run robustness tests for a large subsample of value and equal weighted portfolios (Table 7). Below I have included descriptions of each of the tests carried out.

(1) This is the normal regression model that I included here for the purpose of comparison.

(2) I have originally excluded firms that have a negative book-to-market value i.e. where the firms are theoretically insolvent. Here, I have added them back to see if it makes any difference to the results.

(3) The original sample includes all outliers; under this model I Winzorized 10% of each tail of the returns to see what effect it has on risk adjusted portfolio returns.

(4) To make sure that the results are not driven by a few firms that experience a lot of business outlook adjustments, I have excluded the 10 firms that experienced the most outlook adjustments.

(5) Under the original model a change in business outlook on Friday, would use Monday's return, being the next trading day, in calculating the benchmark portfolio. In this model I have excluded Monday from the sample to see if the results remain unchanged.

(6) Under this model I ran a CAPM regression using Newey-West robust standard errors with a one-day lag to try and overcome any possible autocorrelation and heteroscedasticity.

Table 8.1: *Robustness Tests for the Worsening Portfolio the Day After the BOA (i.e. Benchmark Portfolio)*

	Normal Model		Inclusion		Winsorizing	
	(1)		(2)		(3)	
	$P_{(1,1)}$		$P_{(1,1)}$		$P_{(1,1)}$	
	Improving	Worsening	Improving	Worsening	Improving	Worsening
	Panel A: Full Sample					
Beta	1.113***	1.257***	1.115***	1.264***	1.060***	1.227***
	(9.19)	(11.22)	(9.53)	(11.45)	(9.09)	(11.23)
Alpha	-0.00125	0.00232*	-0.000928	0.00231*	-0.00107	0.00230*
	(-1.25)	(2.52)	(-0.97)	(2.55)	(-1.12)	(2.57)
N	56	56	56	56	56	56
R-sq	0.610	0.700	0.627	0.708	0.605	0.700
	Panel B: Large Firms [Top 50 ME %] - Value Weighted					
Beta	0.460***	1.477***	0.475***	1.477***	0.443***	1.451***
	(3.84)	(11.75)	(3.98)	(11.82)	(3.74)	(11.47)
Alpha	0.000627	0.00339**	0.000656	0.00344**	0.000548	0.00353**
	(0.64)	(3.29)	(0.67)	(3.35)	(0.56)	(3.40)
N	56	56	56	56	56	56
R-sq	0.214	0.719	0.227	0.721	0.205	0.709
	Panel C: Large Firms [Top 50 ME %] - Equal Weighted					
Beta	0.541***	1.488***	0.534***	1.489***	0.521***	1.515***
	(4.71)	(12.33)	(4.66)	(12.38)	4.59	4.60
Alpha	0.000996	0.0031**	0.000887	0.0032**	0.000870	0.00302
	(1.06)	(3.17)	(0.94)	(3.21)	(0.92)	(3.27)
N	56	56	56	56	56	56
R-sq	0.291	0.738	0.286	0.740	0.279	0.728

t statistics in parentheses
=* p<0.05 ** p<0.01 *** p<0.001

This table reports the robust portfolio regressions for the benchmark portfolios of buying an improving portfolio the day after a BOA, holding it for one day and then selling it. As well as the benchmark portfolio of short selling a worsening portfolio the day after the BOA, keeping the position for a day and then closing it out. Panel A shows the results for a full sample value weighted portfolio. Panel B shows the results for portfolios formed from a large subsample of value-weighted firms and Panel C shows these results for a large subsample of equal-weighted firms.

Table 8.2: Continuation of Robustness Tests

	Ex-10 largest		Ex-Monday		Newey-West	
	(4)		(5)		(6)	
	$P_{(1,1)}$		$P_{(1,1)}$		$P_{(1,1)}$	
	Improving	Worsening	Improving	Worsening	Improving	Worsening
	Panel A: Full Sample					
Beta	1.109***	1.260***	1.127***	1.256***	1.113***	1.257***
	(9.42)	(11.28)	(8.36)	(10.55)	(4.66)	(6.19)
Alpha	-0.00120	0.00252**	-0.00154	0.00196	-0.001247	0.00232*
	(-1.24)	(2.75)	(-1.31)	(1.87)	(-1.30)	(2.17)
N	56	56	47	47	56	56
R-sq	0.622	0.702	0.608	0.712	0.610	0.700
	Panel B: Large Firms [Top 50 %] - Value Weighted					
Beta	0.453***	1.481***	0.551**	1.560***	.5412	1.488
	(3.95)	(11.87)	(3.16)	(11.06)	(2.63)	(4.81)
Alpha	0.000688	0.00353**	0.000979	0.00268*	0.000996	0.00314*
	(0.73)	(3.45)	(0.84)	(2.24)	(0.97)	(2.18)
N	56	56	47	47	56	56
R-sq	0.224	0.723	0.196	0.763	0.214	0.719
	Panel C: Large Firms [Top 50 %] - Equal Weighted					
Beta	0.538***	1.488***	0.673***	1.579***	0.4597	1.4768
	(4.71)	(12.39)	(4.09)	(11.62)	(2.38)	(4.74)
Alpha	0.001000	0.00323**	0.000975	0.00278*	0.0006269	0.00392*
	(1.07)	(3.28)	(0.89)	(2.41)	(0.58)	(2.83)
N	56	56	47	47	55	55
R-sq	0.292	0.740	0.290	0.780	0.291	0.738

(1) It is worth noting once more that a full sample of firms produce significant short-selling profits, whereas longing an improving portfolio shows no significance. For the large portfolio the same holds, apart for the fact that the improving portfolio's sign is now positive.

(2) The inclusion of firms with a negative book-to-market value improved the results of the regression. (3) Winzorising led to slightly worse returns, but higher statistical significance. (4) The exclusion of the 10 most dynamic business outlook adjusting firms also improved the results. (5) The exclusion of Monday led to diminishing returns and significance,

this is probably due to a lower sample size and higher volatility. (6) The use of Newey-West standard errors, led to decreased returns, but still remain significant. Overall the results look robust and valid.

To recap, shorting worsening portfolios one day after a business outlook adjustment would produce profitable returns for a full sample of firms as well as for a subsample of large firms. Long-short portfolios are not profitable for a full sample but only profitable for a large subsample of firms, not just the day after an adjustment but also the day before an adjustment, which might be indicative of an event that occurred before the adjustment took place. The subsequent returns can then be due to the public signalling factor of an outlook adjustment that eventually grabs investors' attention, but it can also be due to a confounding event causing both the change in outlook and the ensuing returns.

6 Limitations

Transaction costs can be an issue for the results produced in this study, especially due to the inability of producing significant returns when rebalancing portfolios for longer than a day. I have not gone into the specifics of transaction costs in this study, but the extrapolated annualised returns in Table 3 is quite high and if only a fraction of these returns can be achieved, then transaction costs are unlikely to be much of an issue.

In this study, I cannot guarantee an exclusive causal direction for business outlook to firm returns, I tried to lessen the possible effect by excluding observations that fall within a three-day window of an earnings announcement. Furthermore, it is unknown to what extent a few worker's perception of business outlook is representative of the workforce's perception as a whole. Another major limitation is that workers' voluntary contribution to employer review sites is self-selecting, thus it is not clear whether the data would be the same had it been procured with traditional research methods such as HR case studies and surveys.

More sophisticated investors will focus on fundamental data and pay attention to earnings announcements, financial statements and valuation comparisons for publicly trading companies. All of this information can quickly become overwhelming to the average investors, who tend to be more inclined to follow analyst recommendations. In some way, knowing the health of a public company can be as easy as researching how the employees feel about the company.

A possible issue with the data used in this study, is that the company themselves can meddle with it and spuriously improve their metrics. Glassdoor does, however, have very strict policies and ‘bots’ in place to identify when this is happening so that they can exclude those entries, but it is always possible that some of the entries are fictitious.

7 Future Research

Future research should expand the study by trying to uncover types of disclosures, other than earnings announcements, that might lead to business outlook changes. Events such as a change in corporate ownership, new executives or the announcement of capital expansion projects could all have an effect on business outlook. Business outlook adjustments might therefore just be a proxy for these and similarly significant events.

To control for risk, I made use of the Capital Asset Pricing Model. Although, I also looked at portfolios of different size and identified characteristics such as the portfolio’s book-to-market value, I was not able to adjust returns using the FF3 or FF4 model, due to the factors only being available up and till June 2016. My current dataset unfortunately runs over that period. In this future I suggest making use of these factor models for added robustness. This dataset spans only 56 trading days, I suggest future research to investigate longer periods such as 2-5 years. This will, however, only be possible once enough time has passed for that amount of data to accumulate. In this study I have only included fortune 1000 firms, whilst Glassdoor claims that they have company reviews for over 540,000 firms, which means that this study can easily be expanded to include a more comprehensive set of publicly traded firms.

The relationship between business outlook and earning announcement is also quite interesting. Given that anonymous business outlook ratings are more timely; would they be able to predict earnings hits or misses? Another interesting study would be to test whether the level of business outlook can affect the long-term returns of a firm. In the future, with a larger sample size and longer sample period, it would also be interesting to investigate whether the level of employee stock and option ownership has any effect on the returns earned before an adjustment to see if employees actually trade on their knowledge of the firms' changing outlook.

8 Conclusion

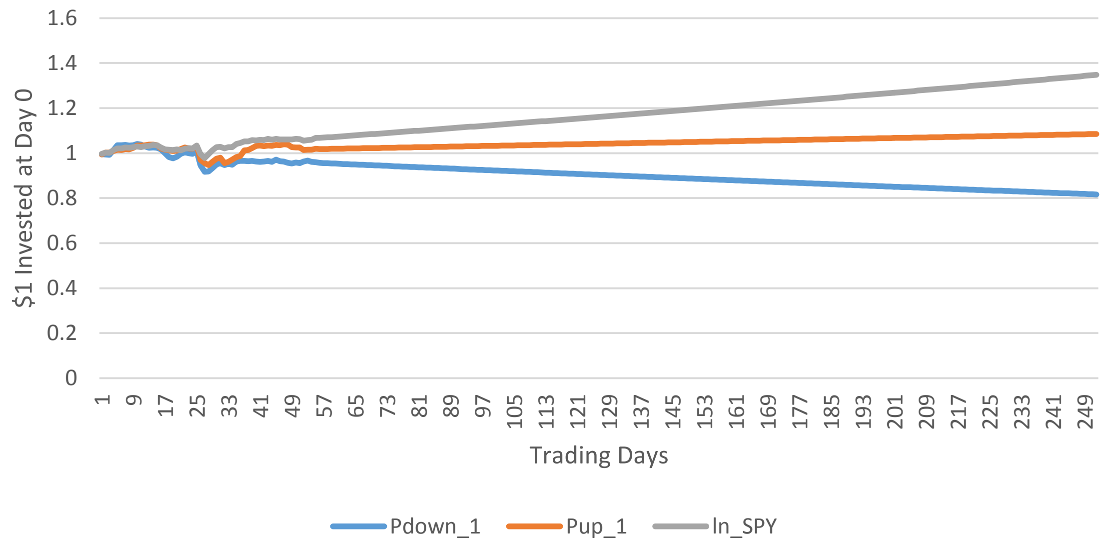
Although this analysis cannot establish a definite causal relationship between employee perception of business outlook and stock returns, there is evidence that a simple short portfolio and a long-short portfolio strategy can produce profitable returns. As per the analysis, portfolios formed the day after a change in business outlook with daily rebalancing performs the best. I also show, by constructing hypothetical pre-formation portfolios, that firms experience returns the day before an adjustment. The abnormal returns after the outlook adjustment can be as a result of the enduring effect of unknown events that cause both the change in outlook and the change in stock price. The subsequent returns can, however, also be as a result of Glassdoor's growing popularity among investors who pay attention to changes in outlook. This study has provided some interesting evidence on the use of social media and employee sourced information in forming profitable investment portfolios, unfortunately, a more conclusive analysis requires more years of data and a larger sample of firms.

Appendix

Figure A1: *Business Outlook Employee Input Options*

The text, "positive", "no-opinion" and "negative" appears both when you hover, and when you select the respective option. A positive and negative opinion leads to a change in the metric. The smallest change is a 1 pp change, normally one vote for a large firm. Glassdoor constructs the metric to place more weight on recent ratings.

Figure A2: *Full sample portfolio value as applied to a $1 investment for the upward and downward changing portfolios, with daily rebalancing over the sample period, including an annual extrapolate to 252 trading days.*



Pdown_1 is the daily raw value-weighted portfolio return of worsening firms rebalanced daily, starting after the BOA. *Pup*$_1$ is similar to *Pdown*$_{1,}$ but for improving firms. The S&P 500 market return is presented as *ln_SPY*. The above graph includes 2 concatenated functions, the first is the cumulative return up and until the sample period ends at day 56, after which the cumulative return gets compounded using the daily geometric average return as calculated from the 56 sample days, to estimate the extrapolated cumulative return for 252 trading days as applied to $1 investment.

***Table A3**: The descriptive statistics table for variables used in value weighted portfolio regressions*

	Improving					Worsening					Difference in Means	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)		
	N	mean	sd	min	max	N	mean	sd	min	max	Difference	t-stat
rm_rf	57	0.000960	0.00815	-0.0368	0.0177	57	0.000960	0.00815	-0.0368	0.0177	-	-
P(1,1)												
Raw Returns	56	0.00184	0.00734	-0.0175	0.0185	55	-0.000655	0.0125	-0.0472	0.0270	0.002495	(1.7649)
Size [ME]	56	59,444	42,262	1,027	177,426	56	56,124	47,961	2,983	281,168	3320	(0.4626)
BM	56	0.380	0.259	0.0223	1.659	56	0.367	0.148	0.105	0.985	0.01300	(0.3019)
Risk-Adjusted Return	56	0.00119	0.00610	-0.0137	0.0267	55	-0.00149	0.0110	-0.0475	0.0269	0.00268	(1.9205)
P(0,1)												
Raw Returns	56	0.00100	0.00916	-0.0309	0.0186	56	0.00229	0.0103	-0.0406	0.0300	-0.00129	(-1.4648)
Size [ME]	56	59,308	42,168	1,039	180,404	56	56,230	48,185	3,015	283,989	3078	(0.4529)
BM	56	0.378	0.255	0.0227	1.630	56	0.367	0.149	0.105	0.994	0.01100	(0.2989)
Risk-Adjusted Return	56	-7.89e-05	0.00582	-0.0226	0.0137	56	0.00103	0.00582	-0.0127	0.0234	-0.00111	(-1.2951)
P(1,1)												
Raw Returns	56	0.0000661	0.0117	-0.0603	0.0266	56	-0.000862	0.0124	-0.0642	0.0205	0.0009281	(0.8367)
Size [ME]	56	59,332	42,178	1,024	181,784	56	56,188	48,234	3,057	282,995	3144	(0.4892)
BM	56	0.378	0.254	0.0225	1.579	56	0.366	0.148	0.105	0.994	0.01200	(0.3104)
Risk-Adjusted Return	56	-0.00125	0.00732	-0.0300	0.0185	56	-0.00232	0.00677	-0.0212	0.0170	0.00107	(0.9730)

This table reports the mean, standard deviation (sd), minimum (min) and maximum (max) values for various measures of the improving and worsening value-weighted portfolios, classified by portfolio formation day, starting one day before the BOA, $P_{(1,1)}$, and ending the day after the BOA $P_{(1,1)}$. This table provides for the market risk premium (*rm_rf*) and the portfolio return adjusted for the risk-free rate (*ri_rf*), as well as the characteristics of the portfolios formed such as the size (market equity) and book-to-market measure (*BM*). I have also included the CAPM risk-adjusted return for the purpose of having the standard errors that contributed to the t-stats as calculated in the regressions. Lastly, this table includes a difference in mean calculation, and the t-test for the long-short portfolio comparing the differences of the risk-adjusted returns.

Table A4: *The descriptive statistics table for variables used in equal weighted portfolio regressions*

	Improving					Worsening					Difference in Means	
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)		
	N	mean	sd	min	max	N	mean	sd	min	max	Difference	t-stat
rm_rf	57	0.000960	0.00815	-0.0368	0.0177	57	0.000960	0.00815	-0.0368	0.0177	-	-
P(-1,1)												
Raw Returns	56	0.00220	0.00938	-0.0277	0.0205	55	0.000682	0.0124	-0.0360	0.0316	0.001518	(1.2284)
Size [ME]	56	24,061	13,731	1,027	62,854	56	25,639	18,670	2,983	116,680	-1578	(-0.5554)
BM	56	0.423	0.199	0.0223	1.282	56	0.438	0.181	0.147	1.162	-0.015	(-0.4142)
Risk-Adjusted Return	56	0.00140	0.00764	-0.0165	0.0328	56	-0.000204	0.0106	-0.0363	0.0290	0.001604	(1.3050)
P(0,1)												
Raw Returns	56	0.00228	0.0103	-0.0402	0.0235	56	0.00242	0.0109	-0.0426	0.0300	-0.00014	(-0.165)
Size [ME]	56	24,049	13,700	1,039	63,358	56	25,682	18,748	3,015	117,469	-1633	(-0.5815)
BM	56	0.421	0.197	0.0227	1.266	56	0.436	0.179	0.145	1.163	-0.015	(-0.4229)
Risk-Adjusted Return	56	0.000988	0.00526	-0.00830	0.0143	56	0.00113	0.00634	-0.0109	0.0233	-0.000142	(-0.1724)
P(1,1)												
Raw Returns	56	-0.0000936	0.0122	-0.0573	0.0200	56	-0.000110	0.0108	-0.0416	0.0219	0.000016	(0.0176)
Size [ME]	56	24,082	13,774	1,024	65,041	56	25,641	18,650	3,057	116,925	-1559	(-0.5638)
BM	56	0.421	0.198	0.0225	1.299	56	0.436	0.181	0.146	1.188	-0.015	(-0.4179)
Risk-Adjusted Return	56	-0.00155	0.00644	-0.0326	0.0114	56	-0.00140	0.00607	-0.0182	0.0163	-0.00015	(-0.1725)

This table reports the mean, standard deviation (sd), minimum (min) and maximum (max) values for various measures of the improving and worsening - equal weighted portfolios, classified by portfolio formation day, starting one day before the , *P(1,1),* and ending the day after the BOA *P(1,1)*. This table provides for the market risk premium (*rm_rf*) and the portfolio return adjusted for the risk-free rate (*ri_rf*), as well as the characteristics of the portfolios formed such as the size (market equity) and book-to-market measure (*BM*). I have also included the risk-adjusted return for the purpose of having the standard errors that contributed to the t-stats as calculated in the regressions. Lastly, this table includes a difference in mean calculation, and the t-test for the long-short portfolio comparing the differences of the risk-adjusted returns.

***Table A5**: Distribution Descriptive Statistics Table for Variables Used in Improving and Worsening Value Weighted Portfolio Regressions*

	Improving						Worsening					
	skewness	p1	p25	p50	p75	p99	skewness	p1	p25	p50	p75	p99
rm_rf	-1.564	-0.0368	-0.00162	0.000971	0.00422	0.0177	-1.564	-0.0368	-0.00162	0.000971	0.00422	0.0177
P(-1,1)												
Raw Returns	-0.0212	-0.0175	-0.00348	0.00224	0.00605	0.0185	-1.086	-0.0472	-0.00671	0.00119	0.00555	0.0270
Size [ME]	0.568	1,027	23,487	48,753	89,780	177,426	2.256	2,983	28,303	44,066	70,958	281,168
BM	2.967	0.0223	0.267	0.338	0.413	1.659	1.425	0.105	0.290	0.362	0.411	0.985
Risk-Adjusted Return	1.142	-0.0137	-0.00310	0.000602	0.00388	0.0267	-1.308	-0.0475	-0.00645	4.47e-05	0.00399	0.0269
P(0,1)												
Raw Returns	-0.755	-0.0309	-0.00415	0.00151	0.00667	0.0186	-0.730	-0.731	-0.0406	-0.00282	0.00125	0.00816
Size [ME]	0.584	1,039	23,530	48,393	89,641	180,404	2.288	3,015	28,498	43,979	71,259	283,989
BM	2.918	0.0227	0.266	0.337	0.416	1.630	1.482	0.105	0.289	0.362	0.406	0.994
Risk-Adjusted Return	-0.801	-0.0226	-0.00269	-7.07e-05	0.00292	0.0137	1.548	-0.0127	-0.00184	-0.00029	0.00311	0.0234
P(1,1)												
Raw Returns	-2.402	-0.0603	-0.00247	0.00175	0.00503	0.0266	-2.435	-0.0642	-0.00461	-0.00160	0.00511	0.0205
Size [ME]	0.582	1,024	23,698	48,795	89,902	181,784	2.271	3,057	28,620	43,719	72,432	282,995
BM	2.816	0.0225	0.266	0.337	0.410	1.579	1.500	0.105	0.290	0.363	0.405	0.994
Risk-Adjusted Return	-1.051	-0.0300	-0.00260	-0.00103	0.00167	0.0185	-0.113	-0.0212	-0.00498	-0.00160	0.00133	0.0170

This table reports the symmetry and percentile distribution measures for improving and worsening firm portfolios, classified by portfolio formation day, starting one day before the BOA , *P(1,1),* and ending the day after the BOA *P(1,1)*. This table provides for the market risk premium (*rm_rf*) and the portfolio return adjusted for the risk-free rate (*ri_rf*), as well as the characteristics of the portfolios formed such as the size (market equity) and book-to-market measure (*BM*). I have also included the risk-adjusted return for the purpose of having the standard errors that contributed to the t-stats as calculated in the regressions. Lastly, this table includes a difference in mean calculation, and the t-test for the long-short portfolio comparing the differences of the risk-adjusted returns.

Table A 6.1: *Descriptive Statistics for OLS Regressions of Daily, Value Weighted Portfolio Returns for Selected Periods of Rebalancing After the Change in Outlook Onwards, Following an Overlapping Rebalancing Strategy*

	Improving					Worsening				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	N	mean	sd	min	max	N	mean	sd	min	max
rm_rf	57	0.000960	0.00815	-0.0368	0.0177	57	0.000960	0.00815	-0.0368	0.0177
P1										
Raw Returns	56	0.000066	0.0117	-0.0605	0.0263	56	-0.00086	0.0123	-0.0644	0.0202
Size [ME]	56	59332.00	42178	1024	181784	56	56188	48234	3057	282995
BM	56	0.378	0.254	0.0225	1.579	56	0.366	0.148	0.105	0.994
P1_4										
Raw Returns	52	0.000422	0.00894	-0.0365	0.0202	52	0.001386	0.00846	-0.0340	0.0187
Size [ME]	52	62828.06	44663	1084	192495	52	59499	51076	3237	299670
BM	52	0.354	0.0493	0.265	0.561	52	0.366	0.0370	0.253	0.471
P1_7										
Raw Returns	49	0.001106	0.00805	-0.0358	0.0191	49	0.001486	0.00881	-0.0377	0.0188
Size [ME]	49	63232.11	44951	1091	193733	49	59881	51405	3258	301597
BM	49	0.355	0.0322	0.302	0.418	49	0.367	0.0217	0.327	0.405
P1_10										
Raw Returns	46	0.001132	0.00819	-0.0361	0.0191	46	0.001346	0.00870	-0.0368	0.0185
Size [ME]	46	62860.09	44686	1085	192594	46	59529	51102	3239	299823
BM	46	0.356	0.0273	0.317	0.415	46	0.365	0.0178	0.334	0.400
P1_20										
Raw Returns	36	0.001166	0.00797	-0.0343	0.0173	36	0.001193	0.00853	-0.0366	0.0176
Size [ME]	36	63756.89	45324	1100	195341	36	60378	51831	3285	304100
BM	36	0.358	0.0188	0.330	0.403	36	0.360	0.00900	0.345	0.391

This table reports the mean, standard deviation (sd), minimum (min) and maximum (max) values for various measures of the improving and worsening portfolios, classified by rebalancing days. This table provides for the market risk premium (*rm_rf*) and the portfolio return adjusted for the risk-free rate (*ri_rf*), as well as the characteristics of the portfolios formed such as the size (market equity) and book-to-market measure (*BM*). I have also included the risk-adjusted return for the purpose of having the standard errors that contributed to the t-stats as calculated in the regressions.

Table A6.2: *Descriptive Statistics for OLS Regressions of Daily, Value Weighted Portfolio Returns for Selected Periods of Rebalancing* *Before* *the Change in Outlook Onwards, Following an Overlapping Rebalancing Strategy.*

	Improving					Worsening				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	N	mean	sd	min	max	N	mean	sd	min	max
rm_rf	57	0.000960	0.00815	-0.0368	0.0177	57	0.000960	0.00815	-0.0368	0.0177
(P-1)										
Raw Returns	56	0.001836	0.00733	-0.0177	0.0183	56	-0.000881	0.0125	-0.0474	0.0268
Size [ME]	56	59444.00	42262	1027	177426	56	56124	47961	2983	281186
BM	56	0.380	0.259	0.0223	1.659	56	0.367	0.148	0.105	0.985
P(-4_-1)										
Raw Returns	52	0.000949	0.00769	-0.0300	0.0179	52	0.000627	0.00930	-0.0383	0.0209
Size [ME]	52	63221.48	44948	1092	188701	52	59691	51009	3173	299054
BM	52	0.342	0.0584	0.178	0.581	52	0.370	0.0433	0.252	0.479
P(-7_-1)										
Raw Returns	49	0.000816	0.00780	-0.0323	0.0185	49	0.000882	0.00890	-0.0386	0.0209
Size [ME]	49	58394.03	41516	1009	174292	49	55133	47114	2930	276219
BM	49	0.344	0.0366	0.244	0.430	49	0.368	0.0229	0.324	0.413
P-10_-1										
Raw Returns	46	0.001138	0.00792	-0.0332	0.0178	46	0.000840	0.00891	-0.0389	0.0192
Size [ME]	46	58317.37	41461	1008	174063	46	55060	47052	2926	275857
BM	46	0.348	0.0219	0.275	0.416	46	0.367	0.0175	0.330	0.407
P-20_-1										
Raw Returns	36	0.001060	0.00788	-0.0328	0.0175	36	0.000813	0.00852	-0.0364	0.0191
Size [ME]	36	58905.08	41879	1018	175817	36	55615	47526	2956	278637
BM	36	0.352	0.00961	0.322	0.370	36	0.364	0.0123	0.343	0.398

This table reports the mean, standard deviation (sd), minimum (min) and maximum (max) values for various measures of the improving and worsening portfolios, classified by rebalancing days. This table provides for the market risk premium (*rm_rf*) and the portfolio return adjusted for the risk-free rate (*ri_rf*), as well as the characteristics of the portfolios formed such as the size (market equity) and book-to-market measure (*BM*).

Table A7: *OLS Regressions of Daily, Value Weighted Portfolio Returns for Selected Periods of Rebalancing After the Change in Outlook Onwards, Tracking Firms that Experience Both Positive and Negative Adjustments in Outlook, Following an Overlapping Rebalancing Strategy.*

	Improving					Worsening				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	P1	P1_4	P1_7	P1_10	P1_20	P1	P1_4	P1_7	P1_10	P1_20
Beta	1.113***	0.927***	0.916***	0.918***	0.932***	1.257***	1.035***	1.027***	1.049***	1.030***
	(9.19)	(24.37)	(28.61)	(30.87)	(32.81)	(11.22)	(29.55)	(39.53)	(48.21)	(42.43)
Alpha	-0.00125	-0.000231	-0.000337	-0.000133	-0.00000566	-0.00232*	-0.000219	-0.000183	-0.000137	-0.000176
	(-1.25)	(-0.75)	(-1.30)	(-0.55)	(-0.02)	(-2.52)	(-0.77)	(-0.87)	(-0.78)	(-0.89)
N	56	52	49	46	36	56	52	49	46	36
R-sq	0.610	0.915	0.937	0.945	0.951	0.700	0.941	0.966	0.977	0.970

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

This table reports the average abnormal portfolio returns corresponding to an upward and downward adjustment in business outlook with less portfolio rebalancing. The dependent variable is the respective portfolio return adjusted with the risk free rate. The independent variable is the market risk premium, being the difference between daily returns on the S&P and the 13-week treasury bond yield as a proxy for the risk free rate. Portfolios (1) to (5) relates to improving business outlook portfolios for (1) daily, (2) 4-day, (3) weekly, (4) 10 and (5) 20-day trading day overlapping portfolio rebalancing. Portfolios (6) to (10) repeats the pattern for the construction of worsening outlook portfolios. The number of observations remain the same due to the large amount of changes that occurred over our sample period. In

Table A8: *OLS Regressions of Daily, Value Weighted Portfolio Returns for selected periods of rebalancing before the day the change in business outlook takes place. Tracking Firms that Experience Both Positive and Negative Adjustments in Outlook, Following an Overlapping Rebalancing Strategy.*

	Improving					Worsening				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	P(-1)	P(-4_-1)	P(-7_-1)	P(-10_-1)	P(-20_-1)	P(-1)	P(-4_-1)	P(-7_-1)	P(-10_-1)	P(-20_-1)
Beta	0.494***	0.959***	0.964***	0.970***	0.956***	0.704***	1.020***	1.027***	1.039***	1.028***
	(4.85)	(27.06)	(30.00)	(36.82)	(41.03)	(3.82)	(30.29)	(39.63)	(37.12)	(37.50)
Alpha	0.00119	-0.000332	-0.000383	-0.000088	-0.000001	-0.00149	-0.000258	0.000179	0.0000514	0.0000266
	(1.42)	(-1.15)	(-1.46)	(-0.41)	(-0.01)	(-0.99)	(-0.94)	(0.85)	(0.23)	(0.12)
N	56	52	49	46	36	56	52	49	46	36
R-sq	0.307	0.930	0.942	0.961	0.968	0.216	0.943	0.966	0.962	0.962

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

This table reports hypothetical average abnormal portfolio returns for the days preceding an upward and downward adjustment in business outlook with less portfolio rebalancing. This gives us an indication as to whether there is a change in returns leading up to the BOA. It also gives an indication of whether insider knowledge can be utilised to generate abnormal returns. The dependent variable is the respective portfolio return adjusted with the risk-free rate. The independent variable is the market risk premium, being the difference between daily returns on the S&P and the 13-week treasury bond yield as a proxy for the risk free rate. Portfolios (1) to (5) relates to improving business outlook portfolios for (1) daily, (2) 4-day, (3) weekly, (4) 10 and (5) 20-day trading day overlapping portfolio rebalancing. Portfolios (6) to (10) repeats the pattern for the construction of worsening outlook portfolios.

Table A9: *OLS Regressions of Daily Value-Weighted Portfolio Returns for Selected Periods of Rebalancing After the Change in Outlook Onwards. Tracking a Subsample of Large Firms that Experience Both Positive and Negative Adjustments in Outlook.*

	Improving					Worsening				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	P1	P1_4	P1_7	P1_10	P1_20	P1	P1_4	P1_7	P1_10	P1_20
Beta	0.460***	0.888***	0.880***	0.881***	0.898***	1.477***	1.001***	0.987***	1.012***	0.994***
	(3.84)	(22.59)	(26.49)	(28.49)	(31.00)	(11.75)	(26.92)	(35.91)	(44.72)	(40.45)
Alpha	0.000627	-0.000203	-0.000366	-0.000132	0.00000493	-0.00339**	-0.000271	-0.000164	-0.000155	-0.000158
	(0.64)	(-0.63)	(-1.36)	(-0.53)	(0.02)	(-3.29)	(-0.90)	(-0.73)	(-0.84)	(-0.79)
N	56	52	49	46	36	56	52	49	46	36
R-sq	0.214	0.903	0.927	0.937	0.946	0.719	0.929	0.959	0.973	0.967

t statistics in parentheses
="* p<0.05 ** p<0.01 *** p<0.001"

This table reports the average abnormal portfolio returns corresponding to an upward and downward adjustment in business outlook with less portfolio rebalancing. The dependent variable is the respective portfolio return adjusted with the risk free rate. The independent variable is the market risk premium, being the difference between daily returns on the S&P 500 and the 13-week treasury bond yield as a proxy for the risk free rate. Portfolios (1) to (5) relates to worsening business outlook portfolios for daily, 4-day, weekly, 10 and 20-day trading day overlapping portfolio rebalancing. Portfolios (6) to (10) repeats the pattern for the construction of worsening outlook portfolios.

Table A10: *OLS Regressions of Daily Value-Weighted Portfolio Returns for selected periods of rebalancing before the day the change in business outlook takes place. Tracking a Subsample of Large Firms that Experience Both Positive and Negative Adjustments in Outlook.*

	Improving					Worsening				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
	P-1	P(-4_-1)	P(-7_-1)	P-10_-1	P-20_-1	P-1	P-4_-1	P-7_-1	P-10_-1	P-20_-1
Beta	0.541***	1.062***	1.045***	1.031***	1.047***	1.488***	1.066***	1.070***	1.112***	1.107***
	(4.71)	(26.32)	(31.07)	(30.78)	(34.63)	(12.33)	(27.07)	(32.52)	(36.30)	(34.76)
Alpha	0.000996	0.0000409	-0.0000244	-0.0000114	0.000117	-0.00314**	0.0000465	-0.0000804	-0.000220	-0.000206
	(1.06)	(0.12)	(-0.09)	(-0.04)	(0.47)	(-3.17)	(0.15)	(-0.30)	(-0.88)	(-0.79)
N	56	52	49	46	36	56	52	49	46	36
R-sq	0.291	0.926	0.946	0.945	0.956	0.738	0.930	0.951	0.960	0.956

t statistics in parentheses
= * p<0.05 ** p<0.01 *** p<0.001

This table reports hypothetical average abnormal portfolio returns for a large subsample of firms for the days preceding an upward and downward adjustment in business outlook with less portfolio rebalancing. This gives us an indication as to whether there is a change in returns leading up to the BOA. It also gives an indication of whether insider knowledge can be utilised to generate abnormal returns. The dependent variable is the respective portfolio return adjusted with the risk-free rate. The independent variable is the market risk premium, being the difference between daily returns on the S&P 500 and the 13-week treasury bond yield as a proxy for the risk free rate. Portfolio (1) to (5) relates to worsening business outlook portfolios for daily, 4-day, weekly, 10 and 20-day trading day overlapping portfolio rebalancing. Portfolio (6) to (10) repeats the pattern for the construction of worsening outlook portfolios.

Top Ranking Firms According To Magnitude of Business Outlook Changes		
	Top Positive BOA Firms	Top Negative BOA Firms
1	Belden	Albemarle
2	Best Buy	Alliant Energy
3	Cisco Systems	American Financial Group
4	Computer Sciences	Ametek
5	Cooper Tire & Rubber	Boeing
6	First Data	DST Systems
7	Kohl's	Foot Locker
8	Lockheed Martin	Genesco
9	Newell Rubbermaid	Goldman Sachs Group
10	Oil States International	Greenbrier Cos.
11	Peabody Energy	Mercury General
12	Phillips 66	News Corp.
13	Pinnacle Entertainment	Oceaneering International
14	Procter & Gamble	Skyworks Solutions
15	Qualcomm	Starbucks
16	Steel Dynamics	State Street Corp.
17	Tupperware Brands	Superior Energy Services
18	UnitedHealth Group	TD Ameritrade Holding
19	Urban Outfitters	Vectren
20	Verizon	WPX Energy

Top Ranking Firms According To Highest Sustained Level of Business Outlook		
	Top Outlook Firms	Bottom Outlook Firms
1	Adobe Systems	AAR
2	Atmos Energy	AK Steel Holding
3	Bristol-Myers Squibb	Alliant Energy
4	Ciena	Apollo Education Group
5	Crown Castle International	Avaya
6	Eastman Chemical	Brink's
7	Equinix	Cabot
8	Expedia	Carpenter Technology
9	Hasbro	Caterpillar
10	Intuitive Surgical	Chemtura
11	Lam Research	Consol Energy
12	Nvidia	Crane
13	Old Dominion Freight Line	Denbury Resources
14	salesforce.com	DuPont
15	Sempra Energy	FMC Technologies
16	Southwest Airlines	Hain Celestial Group
17	Steel Dynamics	Harsco
18	Synopsys	Mercury General
19	Take-Two Interactive Software	Southwestern Energy
20	Ventas	Superior Energy Services

References:

Aspara, J., & Tikkanen, H. (2011). Individuals' Affect-Based Motivations to Invest in Stocks: Beyond Expected Financial Returns and Risks. *Journal of Behavioral Finance, 12*(2), 78-89. doi:10.1080/15427560.2011.575970

Baker, H. K., & Haslem, J. A. (1973). Information needs of individual investors. *Journal of Accountancy,* , 64-69.

Bonsón, E., & Flores, F. (2011). Social media and corporate dialogue: the response of global financial institutions. *Online Information Review, 35*(1), 34-49.

Chamberlain, A. (2015). Does Company Culture Pay Off? Analyzing Stock . - Glassdoor. Retrieved October 8, 2016, from https://www.glassdoor.com/research/studies/does-company-culture-pay-off-analyzing-stock-performance-of-best-places-to-work-companies/.

Chatman, J. A., Caldwell, D. F., O'Reilly, C. A., & Doerr, B. (2013). Parsing Organizational Culture: The Joint Influence of Culture Content and Strength on Performance in High-Technology Firms. *University of California, Berkeley,*

Costa, L. (2010) 'Facebook for Finance.' Institutional Investor 44, 54-93.

Crowe, P. (2016). The world's largest investor is trying to break down the wall. Retrieved October 8, 2016, from http://www.businessinsider.com/how-blackrock-uses-alternative-data-for-impact-investing-2016-6.

Fitzgerald, M. (2016). Is Glassdoor.com useful to make better investments? - Quora. Retrieved October 8, 2016, from https://www.quora.com/Is-Glassdoor-com-useful-to-make-better-investments.

Huang, M., Li, P., Meschke, F., & Guthrie, J. P. (2015). Family firms, employee satisfaction, and corporate performance. *Journal of Corporate Finance, 34*, 108-127.

Hung-Jen Su, Chia-Jung Chang, & Shih-Chieh Chuang. (2010). The Effect of Corporate Image as an Affect Heuristic on Investors' Decision Making. *Asia Pacific Management Review, 15*(3), 453-476. doi:10.6126/APMR.2010.15.3.09

Jame, R., Johnston, R., Markov, S., & Wolfe, M. C. (2016). The Value of Crowdsourced Earnings Forecasts. *Journal of Accounting Research,*

Kothari, S. P., Shu, S., & Wysocki, P. D. (2009). Do managers withhold bad news? *Journal of Accounting Research, 47*(1), 241-276.

Lacy P., Smith D., & Copper, T. (2016). The digital emperor has no clothes - Accenture. Retrieved October 8, 2016, from https://www.accenture.com/t20160915T064252__w__/us-en/_acnmedia/PDF-25/Accenture-Digital-Emperor-POV.pdf.

Lau, M., & Wydick, B. (2014). Does New Information Technology Lower Media Quality? The Paradox of Commercial Public Goods. *Journal of Industry, Competition and Trade, 14*(2), 145-157.

Loh, R. K., & Stulz, R. M. (2011). When are analyst recommendation changes influential? *Review of Financial Studies, 24*(2), 593-627.

Loughlin, C., & Harnisch, E. (2014). The viability of StockTwits and Google Trends to predict the stock market. *Short Report, Spring,*

Miller, G. S., & Skinner, D. J. (2015). The evolving disclosure landscape: How changes in technology, the media, and capital markets are affecting disclosure. *Journal of Accounting Research, 53*(2), 221-239.

Moniz, A. (2016). Inferring Employees' Social Media Perceptions of Corporate Culture and the Link to Firm Value. *Available at SSRN 2768091,*

NZ Herald (2015). Great workplaces make great investments - Business - NZ Herald News. Retrieved October 8, 2016, from http://www.nzherald.co.nz/business/news/article.cfm?c_id=3&objectid=11418617.

Paniagua, J., & Sapena, J. (2014). Business performance and social media: Love or hate? *Business Horizons, 57*(6), 719-728.

Rose, I. (2016). BlackRock's Deborah Winshel: Big Impact Needs Big Data ... Retrieved October 8, 2016, from http://www.institutionalinvestor.com/article/3548164/asset-management-indexing-and-etfs/blackrocks-deborah-winshel-big-impact-needs-big-data.html.

Saxton, G. D., & Anker, A. E. (2013). The aggregate effects of decentralized knowledge production: Financial bloggers and information asymmetries in the stock market. *Journal of Communication, 63*(6), 1054-1069.

Tainer, E. M. *Using economic indicators to improve investment analysis* Wiley Online Library.