Does The Environment Matter?

Investigating the Impact of ESG Ratings on Stock Returns through the Capital Asset Pricing Model and Fama-French Three Factor Model

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I. Introduction

The environment has grown to be an increasingly more concerning topic for the world at large. From considerations of the potential environmental consequences of large national decisions like the Paris Climate Agreement, to firm choice of how to produce, export, extract, and deploy goods and services, and all the way down to the behaviour of individual consumers; what all these stakeholders have in common is: A concern of how their actions can impact the environment. Firms stand out as a subject for analysis as they are key producers in global environmental change. Thus, it is important to analyse the relationship between a firm's incorporation of their impact on the environment through their business decisions. Consequently, one aspect that firms stand to gain from taking environmental concerns seriously is through improving its attraction to investors through its returns. Thus, it is vital for a line of communication between firms and investors to relay how a firm operates regarding environmental concerns.

One such way of communication is through Environmental, Social, and Governance (ESG) ratings. ESG ratings provide a way for stakeholders to understand a firm's approach to managing the risk associated with business decisions that concern the environment, relationship with various stakeholders, and the firm's internal organisation structure (Peterdy, 2022). The method that ESG ratings communicate this information to investors is through an ESG score. An ESG score is quantified through the grading of various categories associated with the risk and impact a firm has concerning the of the three pillars of ESG. Though there are many ESG raters in the market such as Sustainalytics, MSCI, ISS, S&P Global, and more (Larcker et al., 2022); raters communicate this firm-ESG relationship to investors through comprehensive reports which can be purchased or by posting an ESG score online through online articles.

Thus, as environmental concern grows, ESG scoring provides a way to analyse the relationship between a firm's environmental footprint and how it impacts investor attitude towards a firm. This is achieved through the fact that ESG grading and categories are created independent of industry specificities and thus can communicate a score understood regardless of a firm's association to a particular industry. Additionally, one might expect that, in the overall market, investors favour firms with better ESG scores as they may opt for more environmentally sustainable solutions. Interestingly, this prediction may not hold when reviewing the case by industry. One hypothetical example is an industry, such as oil extraction, where it is inherently more difficult to manage the environmental risk associated with business decisions. This inevitably leads to ESG raters granting poor ESG scores for firms belonging to such an industry, At the same time, investors may internalise this relationship and thus ESG scores may not impact the return of such industries at all. On the other hand, firms in the auto manufacturing industry may decide to utilise technology for more fuel-efficient cars, leading to an improved ESG score. As the firm is in more control of the environmental impacts of its production in such an industry, investor perception of ESG scores may have a greater weight in such industries. As such, disentangling this ambiguity through separating by industry allows the study of the relationship between the investor perception of the environmental impacts of an industry and the overall return of that industry.

Thus, my research question is to investigate the impact of ESG ratings on stock returns through the CAPM and Fama-French three factor model through an event study design where the event date is defined as the release of a firm's ESG score by Sustainalytics. Where analyses are conducted on three industries: Automobile and auto components (AUX), textiles, apparel, and luxury goods (TEX), and oil and gas refining and marketing (OGX). This research question has been derived from the growing environmental concern from governments, firms, and consumers, the ability for ESG scores to communicate how firms are behaving in regard to this concern, and the inherent ambiguity of if ESG matters for particular industries.

I applied the CAPM and Fama-French three factor model for stock returns to 39 randomly sampled North American publicly traded firms grouped into the three aforementioned industries. The methodology I utilised is similar to that seen in the paper "Event Studies in Economics and Finance" (MacKinley, 1997). The methodology of my analysis will be outlined later in this paper.

The parameter of the cumulative average abnormal return (CAAR) was estimated through calculating the CAAR for each of the industries over the defined 15-day event window. Interestingly, I found that the p-values associated with each estimated parameter was insignificant. This relationship holds true for each observation in the 15-day event window for each industry.

The results from my investigation are interesting primarily because they demonstrate that the release of ESG scores are an insignificant event in regard to stock return. This is a direct counter to the research reviewed in the next section, where the majority of literature demonstrates that ESG scores are a key component in impacting stock returns. As such, the primary interest of my results lies in determining why the release of ESG scores have come up as insignificant events of industry stock returns. The analysis of the potential reasons for these results are reviewed in depth in the discussion section.

The rest of the paper is organised as such: Section II reviews the existing ESG literature. Section III outlines the sourcing of data, sampling and selection, and the means of analysis. Section IV describes the methodology used to investigate the research question. Section V presents the results, discussion of the analyses, and limitations of this research. Section VI provides concluding remarks and possible extensions of this research.

II. Literature Review

As I investigate the impact the release of ESG scores have on industry returns, it is prudent to understand the perception(s) that investors may have in regard to ESG scores. Accordingly, for these perceptions to materialise it is primary to assume that an investor has a framework of the information about the market available to them. According to Luo (2022), it is realistic to assume that investors may have incomplete information surrounding the market, as such leading to the prevalence of shadow costs. Furthermore, due to these shadow costs, an investor is more willing to hold stocks with better ESG scores due to the positive connotations signalled by better ESG scores (Luo, 2022). Accordingly, a primary reason why this may be the case is due to the finding that firms with better ratings may receive investment with the purpose of further addressing and promoting management of ESG issues (Luo, 2022). Additionally, this further investment into a company with the purpose of addressing ESG issues directly ties in to the liquidity that a firm possesses. As such, during times of crisis, firms with better ESG scores are able to act as a flight-to-liquidity, whereby due to the cyclical positive relationship between investment and better ESG scores, a firm is then able to act as a form of insurance against risk of crisis (Pisani and Russo, 2021; Luo, 2022). As such, there appears to be a clear regard to the safety of investment that these firms propose for investors.

At the same time, research conflicts on whether ESG scores as a predictor variable actually matter for stock returns. On the one hand, some research suggests that ESG scores are an important and significant variable that positively contribute to the stock returns in the context of Indonesian stocks (Trisnowati, Aschani, and Adati, 2021). Whereby, through a stepwise regression method, researchers were able to conclude that the inclusion of ESG scores were able to better model and explain Indonesian stock returns when compared to the inclusion of simply macroeconomic variables (Trisnowati, Aschani, and Adati, 2021). Additionally, though this may be the case for select Indonesian stocks, the relationship exists for US stocks too (Peiris and Evans, 2010). Though ESG scores are positively related to returns, it may be the case that when considering different regions of the world and different markets that the trend may be weaker and even insignificant (Peiris and Evans, 2010). Additionally, some research has suggested that ESG scores impact on returns is more complex than a simple positive relationship. On one hand, for US firms with worsening ESG, it was found that there was a significant reduction in monthly return performance with estimates of -1.0 to -1.4% on average (Shanaev and Ghimire, 2022). In addition, these notable decreases in financial performance related to ESG deterioration were more extreme when ESG leaders were subject to their scores declining (Shanaev and Ghimire, 2022). Moreover, consistent with Peiris and Evans (2010), there was an insignificant though positive trend related between the improvement of a firm's ESG score and their return (Shanaev and Ghimire, 2022). The two relationships identified by Shanaev and Ghimire (2022) were still prevalent even when increasing the event window to account for anticipation and adjustment effects, suggesting the persistence of these relationships.

What's more is that due to there being no single rating institution for ESG scores, there is a plethora of ESG rates, thus different scores and different interpretations of how firms handle and approach the risk associated with ESG issues (Chatterji et al.,2016). Gregory (2022) finds that raters and their ESG scores have a positive relationship to a firm's size. Yet, upon further investigation through quantile regression identifies that the relationship does ot hold for every rater. Rather, the relationship for some individual raters and firm size is being driven by the rating they have assigned to outlier firms (Gregory, 2022). This suggests that though there may be a consistent overall relationship between ESG scores, raters, and firms, similar to Peiris and Evans (2010) findings, the relationship begins to deteriorate due to the difference in ratings between the different raters in the market.

So then, with the conflicting evidence of whether or not ESG scores matter for return and the fact that who rates a firm matters, how exactly are investors supposed to choose their investment portfolio in light of the knowledge of ESG scores for firms? According to Penderson, Fitzgibbons, and Pomorski (2021), institutional investors do in fact incorporate ESG when forming investment portfolios. More importantly, when taking into account ESG scores and issues, the investment decision is more along the lines of what can be described as investor's ideals of a firm's responsibility (Penderson, Fitzgibbons, and Pomorski, 2021). It would appear that investors rather hold companies that promote ESG forward thinking which consequently promote good corporate practice to deal with ESG issues in the future (Penderson, Fitzgibbons, and Pomorski, 2021). At the same time, these ideals are based on the investors belief system upon the management and the long term corporate success of a company in regard to ESG scores and ESG issues rather than just strictly the return on investment (Peiris and Evans, 2010). This suggests that investors seek to invest into firms that are able to mitigate risks over time denoting a corporate structure that allows for the longevity and the safety of investment, the ability of which can be communicated through good and/or improving ESG scores (Peiris and Evans, 2010; Trisnowati, Aschani, and Andati, 2021).

III. Data Sources, Sample Selection, and Analysis Tools

Firstly, the S&P 500 "Corporate Sustainability Assessment [CSA] Invited Universe 2022" (S&P Global, 2022) was used as the primary datasource for identifying firms for analysis. The dataset for eligible firms for analysis was then subgrouped into companies fit for inclusion in the Dow Jones Sustainability Index (DJSI), of whom are invited based on free float asset capitalization in the previous year before invitation (S&P Global, 2022). Furthermore, the dataset was subgrouped into firms eligible for the DJSI North America or DJSI World, this was done in order to ensure that holding period returns and Fama-French factors for the chosen firms were more easily obtainable. As the dataset categorises firms to an industry, industries with 12 or less firms were pruned so as to not use them for analysis. Additionally, a total of three industries were chosen by a random number generator, where the three industries were: AUX, TEX, and OGX. Importantly, S&P defines the automobile and auto components industry as two separate industries, but as the latter is a direct and key input to the former, they are combined to simplify data selection. For brevity of analysis, a total of three industries were chosen. Thereafter, a random number generator was used to select 13 firms from the final subgrouped and pruned firm data set resulting in a total of N=39 firms used for data analysis. Figure 1 below is a table of the chosen firms from the final altered firm data set. Figure 1 includes the firm's name, the event date as defined as the release date of their ESG score by Sustainalytics in addition to their actual score, and lastly the firm's ticker symbol as seen on North American exchanges.

Figure 1. *Firm name and industry, event date, ESG score, and Ticker Symbol*

Firms	Event Date	ESG Score	Ticker
TEX Industry			
Capri Holdings Ltd	Aug 30, 2020	15	CPRI
Carters Inc	Jan 25, 2021	14.8	CRI
Deckers outdoor corp	Mar 17, 2022	13	DECK
Gildan Activewear Inc A	Oct 2, 2020	10.9	GIL
Hanesbrands Inc	Oct 2, 2020	14.5	HBI
Lululemon Athletica inc	Jan 21, 2021	13.2	LULU
NIKE Inc B	Jan 7, 2021	14.8	NKE
PVH Corp	Feb 10, 2021	13.4	PVH
Ralph Lauren Corp A	Jan 7, 2021	13.8	RL
Skechers USA Inc A	Aug 30, 2020	21.9	SKX
Tapestry, Inc	Jan 12, 2021	13.5	TPR
Under Armour Inc A	Nov 24, 2020	15.8	UAA
VF Corp	Dec 12, 2020	11.3	VFC
OGX Industry			
Diamondback Energy Inc	Nov 1, 2020	50.1	FANG
Texas Pacific Land Corporation	Feb 25, 2022	10.5	TPL
Imperial Oil Ltd.	Jan 7, 2021	33.4	IMO
APA Corporation	Feb 23, 2022	45.8	APA
PDC Energy Inc	Mar 13, 2022	48.9	PDCE
Matador Resources Co	Dec 22, 2021	55.9	MTDR
Hess Corp	Nov 17, 2020	29.3	HES
Denbury Inc.	Dec 9, 2021	31.7	DEN
Exxon Mobil Corp	Feb 7, 2021	32.5	XOM
ConocoPhillips	Jan 27, 2021	35.4	COP
Canadian Natural Resources Limited	Jan 27, 2021	33.3	CNQ
Pioneer Natural Resources	Dec 29, 2020	37.4	PXD
Marathon Oil Corp	Nov 11, 2020	42.1	MRO
AUX Industry			
Ford Motor Co	Jan 26, 2021	31.5	F
General Motors Company	May 22, 2020	31.2	GM
Harley-Davidson Inc	Oct 2, 2020	16.3	HOG
Stellantis NV	Feb 18, 2022	24	STLA
Tesla, Inc	Oct 2, 2020	31.1	TSLA
Aptiv plc	Jan 24, 2021	13.9	APTV
Borgwarner Inc	Oct 2, 2020	24	BWA
Tata Motors Ltd	Dec 24, 2020	30.1	TTM
Gentex Corp	Oct 2, 2020	24.5	GNTX
Ferrari NV	Jan 8, 2021	24.8	RACE
Lear Corp	Jan 19, 2021	15.4	LEA
Magna International Inc	Jan 24, 2021	22.8	MG
Toyota Motor Corp	Jan 17, 2021	30.5	TM

The release date of ESG scores was obtained through the Sustainalytics website ESG ratings search function. Each firm's ticker symbol was used as input into this search function in order to gather for firms ESG score release date as their event date.

As this study utilises the CAPM and Fama-French three factor model to model stock returns, the Wharton Research Data Services (WRDS) was used to gather data for these two components. To gather holding period returns, each firm ticker symbol was used in the CRSP Stock Security Files search. A total of 135 observations of holding period were gathered per firm, with 120 trading days prior to the event date, and 15 days after including the event date. Similarly, Fama-French three factors were gathered through WRDS as well. Given each firm's total window, including estimation and event window, Fama-French three factors of excess market return (MKTRF), small-minus-big return (SMB), high-minus-low return (HML), and risk-free return rate (RF), were obtained in guidance with the given window for each firm.

Finally, all dataset curation to files intended for analysis were completed through Microsoft Excel. Analysis and data manipulation in order to derive results, tables, and figures to investigate the research question were done through R studio which uses the R programming language.

IV. Methodology

Firstly, due to the subgrouping and sampling technique described in Section IV to obtain the firms used for analysis, it can be assumed a random sample has been obtained from the finalised curated data set of firms. At the same time, due to this curation, the population that these firms belong to are strictly larger firms with a notable presence in North American markets. This is because of the criteria set out by the S&P 500's CSA invited universe for inclusion. Thus, the analysis was conducted on randomly sampled firms belonging to a population with two primary characteristics: Large firms determined through free float asset capitalization and with a presence or basis in North American markets and exchanges. Furthermore, it is assumed that due to the random sampling technique, that there are no distinct subgroups of firms within the three chosen industries.

Analysis was conducted through a multiple linear regression approach utilising the CAPM and Fama-French three factor approach. There are multiple assumptions underlying this approach: 1) investors are risk averse and determine their investment portfolio through the mean and variance of the portfolio, 2) all investors face the same asset return distribution, 3) all investors may lend or borrow at the same risk free rate (Fama & French, 2004). The Fama-French factors include: excess market return (MKTRF), small-minus-big (SMB), high-minus-low (HML), and the risk free rate of return (RF). These factors were an expansion upon the original CAPM model by William Sharpe (1964) and John Litner (1965). These factors sought to act more as controls to the original model and reign in large but apparent differences between firms in order to better model stock return. Excess market return describes the difference between the market return and risk free rate, the equation for which is defined by MKT-RF = MKTRF. SMB accounts for the trend that smaller market cap firms observe higher returns. HML accounts for firms with high book-to-market ratios that tend to observe a higher return as compared to the market. Thus, equation (1) shows the CAPM and Fama-French three factor linear model of stock return utilised across all firms to obtain predictions for the population parameter explained below. Equation (1) demonstrates that the return for a given period i minus the risk free rate of return i is given by the linear model including the MKTRF, SMB, and HML in period i.

$$RET_i - RF_i = \beta_0 + \beta_1 MKTRF_i + \beta_2 SMB_i + \beta_3 HML_i + \varepsilon_i \tag{1}$$

Data from the 120 trading day estimation window set prior to the event window was used as input to generate a prediction model. This prediction model was used to generate the normal returns for a given firm during its respective 15 trading day event window in respect to the Fama-French three factors observed during that 15 day window. The normal return of each firm during their event window was then subtracted by the respective prediction model's β_0 as the intercept term does not concern the analyses of the sensitivities of the factors and the return of a stock. Next, the abnormal return (abr) for a firm during their event window is calculated by subtracting actual return by the normal return of that same window. This relationship is described in equation (2).

$$abr_t = RET_t - E(RET)_t \tag{2}$$

After abnormal returns are collected for each firm, abnormal returns are averaged by each industry according to the respective period t of the event window. This calculation results in the collection of average abnormal returns (AAR) where in each industry there are 15 observations due to the 15 day event window. Equation (3) demonstrates the calculation of AAR where n connotes a firm where N = 13.

$$AAR_t = \frac{\sum_{i=1}^{N} abr_{i,t}}{N} \tag{3}$$

After AARs are obtained, they are cumulative summed in order to obtain estimates of the population parameter for cumulative average abnormal return (CAAR). The CAAR per industry is calculated by cumulatively summing the AARs for each date in the event window and is calculated by the following:

$$CAAR_{i,t} = \sum_{t\ in\ event\ window} \left(\frac{\sum_{i=1}^{N} abr_{i,t}}{N}\right) \tag{4}$$

As CAAR is the estimate used for testing, it is necessary to obtain its variance and standard error. The number 116 in the following equation was derived from the fact that the degrees of freedom for this equation are the 120 observations (τ_{Es}) subtracted by the 4 coefficients in the prediction model (*K*), 4. As this formula is reliant on the residuals (*u)* from the prediction models they are also included in the calculation. Thus, the variance and standard error of CAAR are found by the following:

$$\sigma^2_{\varepsilon_i} = \frac{\Sigma u_i^2}{\tau_{Es} - K - 1} \tag{5}$$

$$VAR(CAAR_t) = \frac{T}{N^2} * \sum_{i=1}^{n} \sigma^2_{\varepsilon_i} \tag{6}$$

$$SE(CAAR_t) = \sqrt{VAR(CAAR_t)} \tag{7}$$

Finally, the null hypothesis that the release of ESG scores do not impact CAAR as opposed to the alternative hypothesis that release of ESG scores do impact CAAR of the randomly chosen industries was tested. This is summarised in the following:

H_0: $CAAR_t = 0$

H_A: $CAAR_t \neq 0$

The hypothesis was tested at the $\alpha = 0.05$ significance level and rejection was based upon the significance of respective p-values obtained through the t-scores generated by each date in the event window for each industry:

$$t\text{–}score = \frac{CAAR_t - 0}{SE(CAAR_t)} \tag{8}$$

V. Results, Discussion, and Limitations

The table shown in *Figure 2.* demonstrates my numerical findings through the CAPM and Fama-French three factor model analysis on the three industries, TEX, AUX, and OGX. There are no clear signs signifying a relationship between the impact of the release date of an ESG score by Sustainalytics and the impact on industry CAAR values. This lack of relationship is clearly expressed through the lack of statistical significance found from the p-values amongst all industries. What is interesting though, is the fact that, for all industries, t-scores are huddled around 0. This suggests that the release of new market information via the release date of ESG scores by Sustainalytics are in line with the preconceived expectations of returns during the event windows for each industry. The statistical results bear similarities to some of the findings by Peiris and Evans (2010) where researchers studied the impact of the ESG scores itself on return. The key distinction in this research is that the impact of ESG score *release dates* appear to have no impact on market expectations thus no impact on the CAAR of the industries within this research.

Figure 2. *Results table of each industry accompanied by their CAAR over the 15 day event window marked (-4 to 10), along with standard errors, tstats and p-values.*

Event Date	CAAR	SE	t-score	p value
TEX Industry				
-4	0.000	1.260	0.000	0.500
-3	0.007	1.782	0.004	0.501
-2	0.005	2.182	0.002	0.501
-1	0.004	2.520	0.002	0.501
0	-0.003	2.817	-0.001	0.500
1	-0.004	3.086	-0.001	0.499
2	-0.013	3.333	-0.004	0.498
3	-0.018	3.563	-0.005	0.498
4	-0.021	3.780	-0.006	0.498
5	-0.015	3.984	-0.004	0.499
6	-0.012	4.179	-0.003	0.499
7	-0.002	4.364	-0.001	0.500
8	0.005	4.543	0.001	0.500
9	0.004	4.714	0.001	0.500
10	-0.003	4.879	-0.001	0.500
AUX Industry				
-4	0.007	1.089	0.007	0.503
-3	0.008	1.540	0.005	0.502
-2	0.009	1.886	0.005	0.502
-1	0.010	2.178	0.004	0.502
0	0.005	2.435	0.002	0.501
1	0.000	2.667	0.000	0.500
2	-0.005	2.881	-0.002	0.499
3	0.000	3.080	0.000	0.500
4	-0.007	3.267	-0.002	0.499
5	-0.013	3.444	-0.004	0.499
6	-0.017	3.612	-0.005	0.498
7	-0.013	3.772	-0.003	0.499
8	-0.016	3.926	-0.004	0.498
9	-0.024	4.074	-0.006	0.498
10	-0.016	4.217	-0.004	0.499
OGX Industry				
-4	-0.018	1.136	-0.015	0.494
-3	-0.030	1.606	-0.019	0.493
-2	-0.017	1.967	-0.009	0.497
-1	-0.007	2.272	-0.003	0.499
0	-0.023	2.540	-0.009	0.496
1	-0.013	2.782	-0.005	0.498
2	-0.014	3.005	-0.005	0.498
3	-0.002	3.213	-0.001	0.500
4	-0.005	3.408	-0.001	0.499
5	0.023	3.592	0.006	0.503
6	0.025	3.767	0.007	0.503
7	0.037	3.935	0.009	0.504
8	0.043	4.095	0.010	0.504
9	0.030	4.250	0.007	0.503
10	0.028	4.399	0.006	0.503

*p value with signifance at 5% level, $p < 0.05$, denoted with **

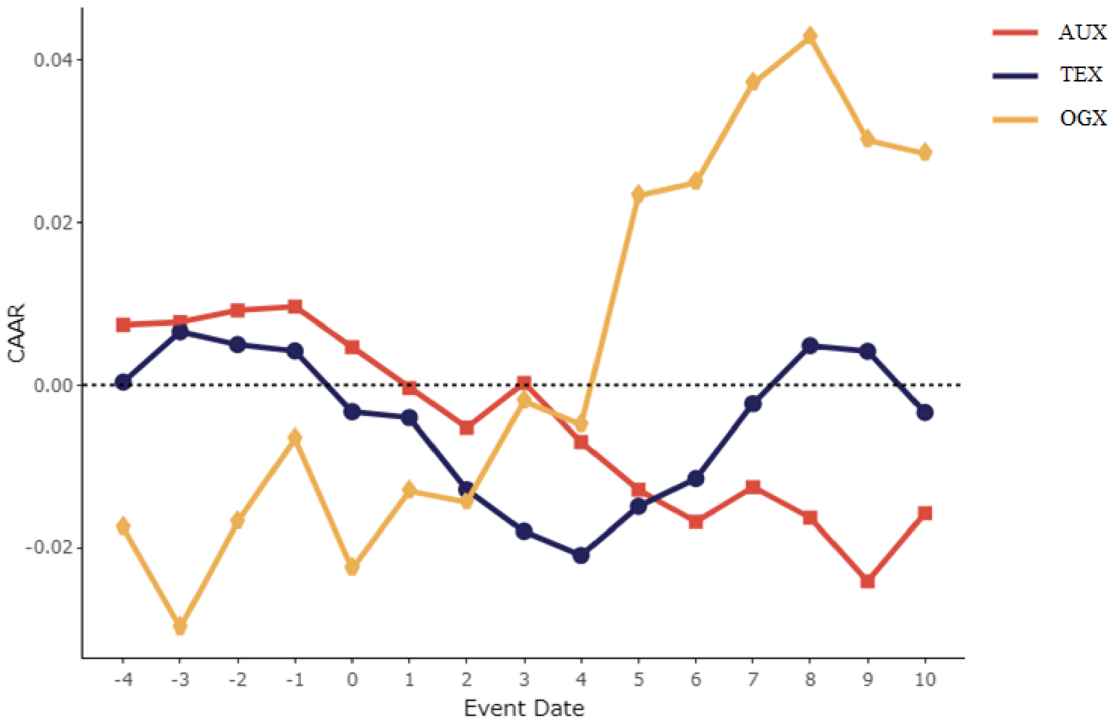

Figure 3. *Graphical depiction of the obtained Cumulative Average Abnormal Returns (CAAR) of each industry.*

As seen in *Figure 3.,* each industry has a discernible trend even before the event date at 0 takes place. To be clear, there is still no real significant, nor even very weak discernible trend in the results of this research. At the same time, the trend exhibited in *Figure 3.* Could be further explored through the expansion of the event window similar to the research by Shanaev and Ghimire (2022). Doing so would have enabled this research to incorporate the role of any anticipation and adjustment effects in regard to the release of the ESG scores by Sustainalytics. Furthermore, due to the insignificance of the results and the marked trends even before the event date, it may be the case that outside events such as press releases and other reports may have compounded into anticipation and adjustment effects well before the release date of the ESG scores.

Additionally, the research by Gregory (2022) may be playing a large but unseen role in these findings. Of all the research cited in this paper, none of them had utilised ESG scores provided by Sustainalytics. For example, each research paper discussed in this paper had used or included MCSI as one of their principal sources of ESG scores. In this case, the lack of significance of these results may suggest that Sustainalytics is too little of a player in regard to the overall ESG raters market and other, more dominant, raters such as MCSI hold a greater weight in the release but also dictation of ESG scoring of firms.

Furthermore, a limitation of this research is the poorly defined variable of the release date of ESG scores. This is because the release of an ESG score of a firm could entail three possible outcomes, improvement, degradation, or maintaining the same score. As such, by grouping firms into industries and taking their average results without regarding the outcome of the ESG score, you inevitably will have a lack of direction in results. A few firms could have improved, while others maintained, and still some others worsened. Thus, it would have been much more effective to further define the event variable to something that takes into account the outcome of the release date of an ESG score for a firm. Whether it pertains to firms where all scores improved, then categorise by industry and then compare to the same industry with firms that only worsened in score. Thus, the actual impact of the release date of the ESG score would be much clearer to discern.

Moreover, this research does not have any form of robustness or further explorations into the reason why the scores are insignificant. Simply put, the exploration through the CAPM and Fama-French three factor model was the empirical analysis of this paper in its totality. As compared to other research which attempted to investigate their results further such as by implementing different regression methods and robustness checks on their model(s) (Shanaev and Ghimire, 2021; Luo, 2022).

VI. Conclusion and Extensions

All in all, the results of this paper are rather anticlimactic. Through a CAPM and Fama-French three factor model it was found that the impact of the release date of ESG scores by Sustainalytics had no significant impact nor trend on the three industries of: Automobile and auto components (AUX), textiles, apparel, and luxury goods (TEX), and oil and gas refining and marketing (OGX). As for the reason for the insignificant results, it is pointed out that it may be due to the myriad of limitations inherent within the design of this research. From lack of robustness checks, to lack of further investigation into results by expanding the event window, to the fact that the chosen rater for ESG scores may have no weight in the ESG market. At the same time, the results are interesting precisely because they are insignificant as they contradict established findings in research. As such, further investigations regarding this research may be of more interest. One such further exploration, mentioned briefly previously, could be the further development of the definition for the event. One such case being to investigate intra industry reaction to the release of ESG scores. This could be done by following the same methodology in this paper, but instead to define the event as the release date of positive scores vs. negative scores and then group firms within an industry according to that positive or negative outcome of the release of ESG scores. This idea could even be further expanded upon by comparing the intra-industry differences to other industries thereby allowing for the comparison of the sensitivity of improving vs degrading ESG scores and different industries. Overall, further investigations on the impact that ESG has on investors and firms may be beneficial not only to these two stakeholders but for the environment as well by putting a focus on ESG issues and their impact on the market today and through time.

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Appendix A. R code used for empirical analysis

```
install.packages("tidyverse")
install.packages("plotly")
library(readr)
library(ggplot2)
library(tidyr)
library(plotly)
#Read in the data
AUTO <- read_csv("Auto.csv")
TEXTILES <- read_csv("Textiles.csv")
OIL <- read_csv("Oil UPST.csv")
#######################################################################################

#Modular linear regression functions need 13, for each firm
#event window -4,-3,-2,-1,0,1,2,3,4,5,6,7,8,9,10 (15 days)

get_reg1 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(1:120))
get_reg2 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(136:255))
get_reg3 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(271:390))
get_reg4 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(406:525))
get_reg5 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(541:660))
get_reg6 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(676:795))
get_reg7 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(811:930))
get_reg8 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(946:1065))
get_reg9 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(1081:1200))
get_reg10 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(1216:1335))
get_reg11 <- function(x) lm(RET-rf ~ mktrf + smb + hml, data=x, subset = c(1351:1470))
get_reg12 <- function(x) lm(RET-rf~ mktrf + smb + hml, data=x, subset = c(1486:1605))
get_reg13 <- function(x) lm(RET-rf~ mktrf + smb + hml, data=x, subset = c(1621:1740))

#######################################################################################
#regs for auto
auto1 <- get_reg1(AUTO)
auto2 <- get_reg2(AUTO)
auto3 <- get_reg3(AUTO)
auto4 <- get_reg4(AUTO)
auto5 <- get_reg5(AUTO)
auto6 <- get_reg6(AUTO)
auto7 <- get_reg7(AUTO)
auto8 <- get_reg8(AUTO)
auto9 <- get_reg9(AUTO)
auto10 <- get_reg10(AUTO)
auto11 <- get_reg11(AUTO)
auto12 <- get_reg12(AUTO)
auto13 <- get_reg13(AUTO)

#regs for textiles
text1 <- get_reg1(TEXTILES)
text2 <- get_reg2(TEXTILES)
text3 <- get_reg3(TEXTILES)
text4 <- get_reg4(TEXTILES)
text5 <- get_reg5(TEXTILES)
text6 <- get_reg6(TEXTILES)
text7 <- get_reg7(TEXTILES)
text8 <- get_reg8(TEXTILES)
text9 <- get_reg9(TEXTILES)
text10 <- get_reg10(TEXTILES)
text11 <- get_reg11(TEXTILES)
text12 <- get_reg12(TEXTILES)
```

```
text13 <- get_reg13(TEXTILES)

#regs for oil
oil1 <- get_reg1(OIL)
oil2 <- get_reg2(OIL)
oil3 <- get_reg3(OIL)
oil4 <- get_reg4(OIL)
oil5 <- get_reg5(OIL)
oil6 <- get_reg6(OIL)
oil7 <- get_reg7(OIL)
oil8 <- get_reg8(OIL)
oil9 <- get_reg9(OIL)
oil10 <- get_reg10(OIL)
oil11 <- get_reg11(OIL)
oil12 <- get_reg12(OIL)
oil13 <- get_reg13(OIL)
###################################################################################
#Modular prediction functions need 13, for each firm

#arguments take a regresssion (x) and a dataset (y)
predictionfx1 <- function(x,y) predict.lm(x, as.data.frame(y[c(121:135),c(4:7)]))
predictionfx2 <- function(x,y) predict.lm(x, as.data.frame(y[c(256:270),c(4:7)]))
predictionfx3 <- function(x,y) predict.lm(x, as.data.frame(y[c(391:405),c(4:7)]))
predictionfx4 <- function(x,y) predict.lm(x, as.data.frame(y[c(526:540),c(4:7)]))
predictionfx5 <- function(x,y) predict.lm(x, as.data.frame(y[c(661:675),c(4:7)]))
predictionfx6 <- function(x,y) predict.lm(x, as.data.frame(y[c(796:810),c(4:7)]))
predictionfx7 <- function(x,y) predict.lm(x, as.data.frame(y[c(931:945),c(4:7)]))
predictionfx8 <- function(x,y) predict.lm(x, as.data.frame(y[c(1066:1080),c(4:7)]))
predictionfx9 <- function(x,y) predict.lm(x, as.data.frame(y[c(1201:1215),c(4:7)]))
predictionfx10 <- function(x,y) predict.lm(x, as.data.frame(y[c(1336:1350),c(4:7)]))
predictionfx11 <- function(x,y) predict.lm(x, as.data.frame(y[c(1471:1485),c(4:7)]))
predictionfx12 <- function(x,y) predict.lm(x, as.data.frame(y[c(1606:1620),c(4:7)]))
predictionfx13 <- function(x,y) predict.lm(x, as.data.frame(y[c(1741:1755),c(4:7)]))

#predictions for auto
predauto1 <- predictionfx1(auto1, AUTO)
predauto2 <- predictionfx2(auto2, AUTO)
predauto3 <- predictionfx3(auto3, AUTO)
predauto4 <- predictionfx4(auto4, AUTO)
predauto5 <- predictionfx5(auto5, AUTO)
predauto6 <- predictionfx6(auto6, AUTO)
predauto7 <- predictionfx7(auto7, AUTO)
predauto8 <- predictionfx8(auto8, AUTO)
predauto9 <- predictionfx9(auto9, AUTO)
predauto10 <- predictionfx10(auto10, AUTO)
predauto11 <- predictionfx11(auto11, AUTO)
predauto12 <- predictionfx12(auto12, AUTO)
predauto13 <- predictionfx13(auto13, AUTO)

#predictions for textiles
predtext1 <- predictionfx1(text1, TEXTILES)
predtext2 <- predictionfx2(text2, TEXTILES)
predtext3 <- predictionfx3(text3, TEXTILES)
predtext4 <- predictionfx4(text4, TEXTILES)
predtext5 <- predictionfx5(text5, TEXTILES)
predtext6 <- predictionfx6(text6, TEXTILES)
predtext7 <- predictionfx7(text7, TEXTILES)
predtext8 <- predictionfx8(text8, TEXTILES)
predtext9 <- predictionfx9(text9, TEXTILES)
predtext10 <- predictionfx10(text10, TEXTILES)
```

```
predtext11 <- predictionfx11(text11, TEXTILES)
predtext12 <- predictionfx12(text12, TEXTILES)
predtext13 <- predictionfx13(text13, TEXTILES)

#predictions for oil
predoil1 <- predictionfx1(oil1, OIL)
predoil2 <- predictionfx2(oil2, OIL)
predoil3 <- predictionfx3(oil3, OIL)
predoil4 <- predictionfx4(oil4, OIL)
predoil5 <- predictionfx5(oil5, OIL)
predoil6 <- predictionfx6(oil6, OIL)
predoil7 <- predictionfx7(oil7, OIL)
predoil8 <- predictionfx8(oil8, OIL)
predoil9 <- predictionfx9(oil9, OIL)
predoil10 <- predictionfx10(oil10, OIL)
predoil11 <- predictionfx11(oil11, OIL)
predoil12 <- predictionfx12(oil12, OIL)
predoil13 <- predictionfx13(oil13, OIL)
##################################################################################
#remove intercepts from predictions

#predictions for auto
pauto1 <- sapply(predauto1, function(x) x-auto1[["coefficients"]][["(Intercept)"]])
pauto2 <- sapply(predauto2, function(x) x-auto2[["coefficients"]][["(Intercept)"]])
pauto3 <- sapply(predauto3, function(x) x-auto3[["coefficients"]][["(Intercept)"]])
pauto4 <- sapply(predauto4, function(x) x-auto4[["coefficients"]][["(Intercept)"]])
pauto5 <- sapply(predauto5, function(x) x-auto5[["coefficients"]][["(Intercept)"]])
pauto6 <- sapply(predauto6, function(x) x-auto6[["coefficients"]][["(Intercept)"]])
pauto7 <- sapply(predauto7, function(x) x-auto7[["coefficients"]][["(Intercept)"]])
pauto8 <- sapply(predauto8, function(x) x-auto8[["coefficients"]][["(Intercept)"]])
pauto9 <- sapply(predauto9, function(x) x-auto9[["coefficients"]][["(Intercept)"]])
pauto10 <- sapply(predauto10, function(x) x-auto10[["coefficients"]][["(Intercept)"]])
pauto11 <- sapply(predauto11, function(x) x-auto11[["coefficients"]][["(Intercept)"]])
pauto12 <- sapply(predauto12, function(x) x-auto12[["coefficients"]][["(Intercept)"]])
pauto13 <- sapply(predauto13, function(x) x-auto13[["coefficients"]][["(Intercept)"]])

#predictions for textiles
ptext1 <- sapply(predtext1, function(x) x-text1[["coefficients"]][["(Intercept)"]])
ptext2 <- sapply(predtext2, function(x) x-text2[["coefficients"]][["(Intercept)"]])
ptext3 <- sapply(predtext3, function(x) x-text3[["coefficients"]][["(Intercept)"]])
ptext4 <- sapply(predtext4, function(x) x-text4[["coefficients"]][["(Intercept)"]])
ptext5 <- sapply(predtext5, function(x) x-text5[["coefficients"]][["(Intercept)"]])
ptext6 <- sapply(predtext6, function(x) x-text6[["coefficients"]][["(Intercept)"]])
ptext7 <- sapply(predtext7, function(x) x-text7[["coefficients"]][["(Intercept)"]])
ptext8 <- sapply(predtext8, function(x) x-text8[["coefficients"]][["(Intercept)"]])
ptext9 <- sapply(predtext9, function(x) x-text9[["coefficients"]][["(Intercept)"]])
ptext10 <- sapply(predtext10, function(x) x-text10[["coefficients"]][["(Intercept)"]])
ptext11 <- sapply(predtext11, function(x) x-text11[["coefficients"]][["(Intercept)"]])
ptext12 <- sapply(predtext12, function(x) x-text12[["coefficients"]][["(Intercept)"]])
ptext13 <- sapply(predtext13, function(x) x-text13[["coefficients"]][["(Intercept)"]])

#predictions for oil
poil1 <- sapply(predoil1, function(x) x-oil1[["coefficients"]][["(Intercept)"]])
poil2 <- sapply(predoil1, function(x) x-oil2[["coefficients"]][["(Intercept)"]])
poil3 <- sapply(predoil1, function(x) x-oil3[["coefficients"]][["(Intercept)"]])
poil4 <- sapply(predoil1, function(x) x-oil4[["coefficients"]][["(Intercept)"]])
poil5 <- sapply(predoil1, function(x) x-oil5[["coefficients"]][["(Intercept)"]])
poil6 <- sapply(predoil1, function(x) x-oil6[["coefficients"]][["(Intercept)"]])
poil7 <- sapply(predoil1, function(x) x-oil7[["coefficients"]][["(Intercept)"]])
poil8 <- sapply(predoil1, function(x) x-oil8[["coefficients"]][["(Intercept)"]])
```

```
poil9 <- sapply(predoil1, function(x) x-oil9[["coefficients"]][["(Intercept)"]])
poil10 <- sapply(predoil1, function(x) x-oil10[["coefficients"]][["(Intercept)"]])
poil11 <- sapply(predoil1, function(x) x-oil11[["coefficients"]][["(Intercept)"]])
poil12 <- sapply(predoil1, function(x) x-oil12[["coefficients"]][["(Intercept)"]])
poil13 <- sapply(predoil1, function(x) x-oil13[["coefficients"]][["(Intercept)"]])
###################################################################################

#obtain abnormal returns == actual - predicted
#x is the dataset, y is the predicted value
getab1 <- function(x,y) mapply('-', unlist(lapply(x[c(121:135),3], as.numeric)), y)
getab2 <- function(x,y) mapply('-', unlist(lapply(x[c(256:270),3], as.numeric)), y)
getab3 <- function(x,y) mapply('-', unlist(lapply(x[c(391:405),3], as.numeric)), y)
getab4 <- function(x,y) mapply('-', unlist(lapply(x[c(526:540),3], as.numeric)), y)
getab5 <- function(x,y) mapply('-', unlist(lapply(x[c(661:675),3], as.numeric)), y)
getab6 <- function(x,y) mapply('-', unlist(lapply(x[c(796:810),3], as.numeric)), y)
getab7 <- function(x,y) mapply('-', unlist(lapply(x[c(931:945),3], as.numeric)), y)
getab8 <- function(x,y) mapply('-', unlist(lapply(x[c(1066:1080),3], as.numeric)), y)
getab9 <- function(x,y) mapply('-', unlist(lapply(x[c(1201:1215),3], as.numeric)), y)
getab10 <- function(x,y) mapply('-', unlist(lapply(x[c(1336:1350),3], as.numeric)), y)
getab11 <- function(x,y) mapply('-', unlist(lapply(x[c(1471:1485),3], as.numeric)), y)
getab12 <- function(x,y) mapply('-', unlist(lapply(x[c(1606:1620),3], as.numeric)), y)
getab13 <- function(x,y) mapply('-', unlist(lapply(x[c(1741:1755),3], as.numeric)), y)

#ab returns for auto
abauto1 <- getab1(AUTO, pauto1)
abauto2 <- getab2(AUTO, pauto2)
abauto3 <- getab3(AUTO, pauto3)
abauto4 <- getab4(AUTO, pauto4)
abauto5 <- getab5(AUTO, pauto5)
abauto6 <- getab6(AUTO, pauto6)
abauto7 <- getab7(AUTO, pauto7)
abauto8 <- getab8(AUTO, pauto8)
abauto9 <- getab9(AUTO, pauto9)
abauto10 <- getab10(AUTO, pauto10)
abauto11 <- getab11(AUTO, pauto11)
abauto12 <- getab12(AUTO, pauto12)
abauto13 <- getab13(AUTO, pauto13)

#ab returns for textiles
abtext1 <- getab1(TEXTILES, ptext1)
abtext2 <- getab2(TEXTILES, ptext2)
abtext3 <- getab3(TEXTILES, ptext3)
abtext4 <- getab4(TEXTILES, ptext4)
abtext5 <- getab5(TEXTILES, ptext5)
abtext6 <- getab6(TEXTILES, ptext6)
abtext7 <- getab7(TEXTILES, ptext7)
abtext8 <- getab8(TEXTILES, ptext8)
abtext9 <- getab9(TEXTILES, ptext9)
abtext10 <- getab10(TEXTILES, ptext10)
abtext11 <- getab11(TEXTILES, ptext11)
abtext12 <- getab12(TEXTILES, ptext12)
abtext13 <- getab13(TEXTILES, ptext13)

#ab returns for oil
aboil1 <- getab1(OIL, poil1)
aboil2 <- getab2(OIL, poil2)
aboil3 <- getab3(OIL, poil3)
aboil4 <- getab4(OIL, poil4)
aboil5 <- getab5(OIL, poil5)
aboil6 <- getab6(OIL, poil6)
```

```
aboil7 <- getab7(OIL, poil7)
aboil8 <- getab8(OIL, poil8)
aboil9 <- getab9(OIL, poil9)
aboil10 <- getab10(OIL, poil10)
aboil11 <- getab11(OIL, poil11)
aboil12 <- getab12(OIL, poil12)
aboil13 <- getab13(OIL, poil13)
################################################################################

#create dataframe for each industry

#auto df
ABautodf <- data.frame(abauto1, abauto2, abauto3, abauto4, abauto5, abauto6,
                   abauto7, abauto8, abauto9, abauto10, abauto11, abauto12,
                   abauto13)
rownames(ABautodf) <- lapply(c(-4:10), toString)
colnames(ABautodf) <- c("GM", 'APTV', 'F', 'HOG', 'STLA', 'TSLA', 'BWA', 'TTM',
                    'GNTX', 'LEA', 'MG', 'TM', 'RACE')

#textile df
ABtextdf <- data.frame(abtext1, abtext2, abtext3, abtext4, abtext5, abtext6,
                   abtext7, abtext8, abtext9, abtext10, abtext11, abtext12,
                   abtext13)
rownames(ABtextdf) <- lapply(c(-4:10), toString)
colnames(ABtextdf) <- c('CPRI','PVH', 'VFC', 'NKE', 'DECK', 'RL', 'GIL', 'SKX',
                    'TPR', 'CRI', 'UAA', 'HBI', 'LULU')

#oil df
ABoildf <- data.frame(aboil1, aboil2, aboil3, aboil4, aboil5, aboil6, aboil7,
                  aboil8, aboil9, aboil10, aboil11, aboil12, aboil13)
rownames(ABoildf) <- lapply(c(-4:10), toString)
colnames(ABoildf) <- c('XOM', 'MTDR', 'FANG', 'COP', 'TPL', 'MRO', 'DEN', 'HES',
                   'IMO', 'APA', 'PDCE', 'CNQ', 'PXD')


################################################################################

#create df with AAR in each industry

dfAARauto <- data.frame(rowSums(sapply(ABautodf[1:13], as.numeric))/13)
dfAARtext <- data.frame(rowSums(sapply(ABtextdf[1:13], as.numeric))/13)
dfAARoil <- data.frame(rowSums(sapply(ABoildf[1:13], as.numeric))/13)

#create df with CAAR in each industry

dfCAARauto <- data.frame(cumsum(dfAARauto))
dfCAARtext <- data.frame(cumsum(dfAARtext))
dfCAARoil <- data.frame(cumsum(dfAARoil))

#AAR with CAAR

dfAARCAARauto <- data.frame(dfAARauto, dfCAARauto)
rownames(dfAARCAARauto) <- c(-4:10)
colnames(dfAARCAARauto) <- c("AAR auto", "CAAR auto")

dfAARCAARtext <- data.frame(dfAARtext, dfCAARtext)
rownames(dfAARCAARtext) <- c(-4:10)
colnames(dfAARCAARtext) <- c("AAR textiles", "CAAR textiles")

dfAARCAARoil <- data.frame(dfAARoil, dfCAARoil)
```

```
rownames(dfAARCAARoil) <- c(-4:10)
colnames(dfAARCAARoil) <- c("AAR oil", "CAAR oil")

#create dfCAAR all included

dfCAAR <- data.frame(dfCAARauto, dfCAARtext, dfCAARoil)
rownames(dfCAAR) <- lapply(c(-4:10), toString)
colnames(dfCAAR) <- c('AUTO', 'TEXTILES', 'OIL')

################################################################################

#obtain varCAAR's

#varCAAR auto
varCAARauto <- function(x) (x/116*13^2)*
  sum(unlist(lapply(lapply(lapply(list(auto1, auto2, auto3, auto4, auto5,
                                auto6,auto7,auto8,auto9,auto10,auto11,
                                auto12,auto13), resid), function(x) x^2), sum)))

#varCAAR text
varCAARtext <- function(x) (x/116*13^2)*
  sum(unlist(lapply(lapply(lapply(list(text1, text2, text3, text4, text5, text6,
                                text7,text8,text9,text10,text11,text12,
                                text3), resid), function(x) x^2), sum)))

#varCAAR oil
varCAARoil <- function(x) (x/116*13^2)*
  sum(unlist(lapply(lapply(lapply(list(oil1, oil2, oil3, oil4, oil5, oil6, oil7,
                                oil8,oil9,oil10,oil11,oil12,oil13),
                              resid), function(x) x^2), sum)))


#obtain seCAAR's

seCAARauto <- function(x) sqrt(varCAARauto(x))
seCAARtext <- function(x) sqrt(varCAARtext(x))
seCAARoil <- function(x) sqrt(varCAARoil(x))

#seCAAR lists

selistauto <- seCAARauto(1:15)
selisttext <- seCAARtext(1:15)
selistoil <- seCAARoil(1:15)

#obtain t tests

TCAARauto <- (dfCAAR[,1]-0)/selistauto
TCAARtext <-(dfCAAR[,2]-0)/selisttext
TcAARoil <-(dfCAAR[,3]-0)/selistoil

#obtain p tests
p_test_auto <- function(x) pt(TCAARauto[x], df=116)
p_test_text <- function(x) pt(TCAARtext[x], df=116)
p_test_oil <- function(x) pt(TcAARoil[x], df=116)
################################################################################

#Normal returns (predicted)
dfnrauto <- data.frame(pauto1, pauto2, pauto3, pauto4, pauto5, pauto6,
                   pauto7, pauto8, pauto9, pauto10, pauto11, pauto12,
                   pauto13)
```

```
dfANRauto <- data.frame(rowSums(sapply(dfnrauto[1:13], as.numeric))/13)

dfCANRauto <- data.frame(cumsum(dfANRauto))


dfnrtext <- data.frame(ptext1, ptext2, ptext3, ptext4, ptext5, ptext6, ptext7,
                    ptext8, ptext9, ptext10, ptext11, ptext12, ptext13)

dfANRtext <- data.frame(rowSums(sapply(dfnrtext[1:13], as.numeric))/13)

dfCANRtext <- data.frame(cumsum(dfANRtext))


dfnroil <- data.frame(poil1, poil2, poil3, poil4, poil5, poil6, poil7, poil8,
                   poil9, poil10, poil11, poil12, poil13)

dfANRoil <- data.frame(rowSums(sapply(dfnroil[1:13], as.numeric))/13)

dfCANRoil <- data.frame(cumsum(dfANRoil))
################################################################################
#create final data frame

dffinal <- data.frame(Date = -4:10,
                   dfCAARauto, selistauto, TCAARauto, p_test_auto(1:15), p_test_auto(1:15)<0.05,
                   dfCAARtext, selisttext, TCAARtext, p_test_text(1:15), p_test_text(1:15)<0.05,
                   dfCAARoil, selistoil, TcAARoil, p_test_oil(1:15),  p_test_oil(1:15)<0.05)
rownames(dffinal) <- lapply(c(-4:10), toString)
colnames(dffinal) <- c('DATE', 'CAAR_auto', 'SE_auto', 'Tscore_auto', 'pval_auto', 'auto_alpha<0.05',
                    'CAAR_textiles', 'SE_textiles', 'Tscore_textiles', 'pval_textiles', 'textiles_alpha<0.05',
                    'CAAR_oil', 'SE_oil', 'Tscore_oil', 'pval_oil', 'oil_alpha<0.05')

View(dffinal)

number_ticks <- function(n) {function(limits) pretty(limits, n)}

plotly::ggplotly(
  dffinal %>%
    ggplot(aes(x=DATE)) +
    scale_x_continuous(breaks=number_ticks(20)) +
    scale_color_manual(name = "", values = c('CAAR_auto' = '#DC4E40', 'CAAR_textiles' = '#25245D',
                                      'CAAR_oil' = '#EFB156')) +
    geom_point(aes(y=CAAR_auto), size = 0.5, colour = '#DC4E40', shape = 15,
            stroke =2, fill = "#DC4E40") +
    geom_point(aes(y=CAAR_textiles), size = 1.1, colour = '#25245D', shape = 16,
            stroke =2, fill = "#25245D") +
    geom_point(aes(y=CAAR_oil), size = 1, colour = '#EFB156', shape = 17,
            stroke =2, fill = "#EFB156") +
    geom_line(aes(y=CAAR_auto, colour = 'CAAR_auto'), lwd=1) +
    geom_line(aes(y=CAAR_textiles, colour = 'CAAR_textiles'),lwd=1) +
    geom_line(aes(y=CAAR_oil, colour = 'CAAR_oil'),lwd=1) +
    labs(y = "CAAR",
       x = "Event Date") +
    geom_hline(yintercept=0, linetype='dotted', col = 'black') +
    facet_wrap(~ variable) +
    theme_classic()
)
```