# IN THE LINE OF FIRE

## A STUDY OF MARKET EFFICIENCY IN THE CONTEXT OF WILDFIRES AND STOCK MARKET REACTIONS

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**In the Line of Fire: A Study of Market Efficiency in the Context of Wildfires and Stock Market Reactions**

Abstract:

Climate research finds that climate change and raising global temperatures increase the risk and severity of wildfires. However, the impact varies substantially based on geographical location and causes a dispersion in wildfire trends. Utilizing data from 14 countries, we investigate if wildfire severity trends have a material impact on the profitability of the forestry and paper & pulp (P&P) industries and whether the stock market is efficiently pricing these trends. We find that a poor wildfire trend ranking for a country forecasts lower profitability growth and that the market responds efficiently in terms of correctly pricing this climate change-related risk.

Keywords:

Climate Disaster Events, Wildfires, Fire Weather Index, Fire Severity Rating, Efficient Market Hypothesis

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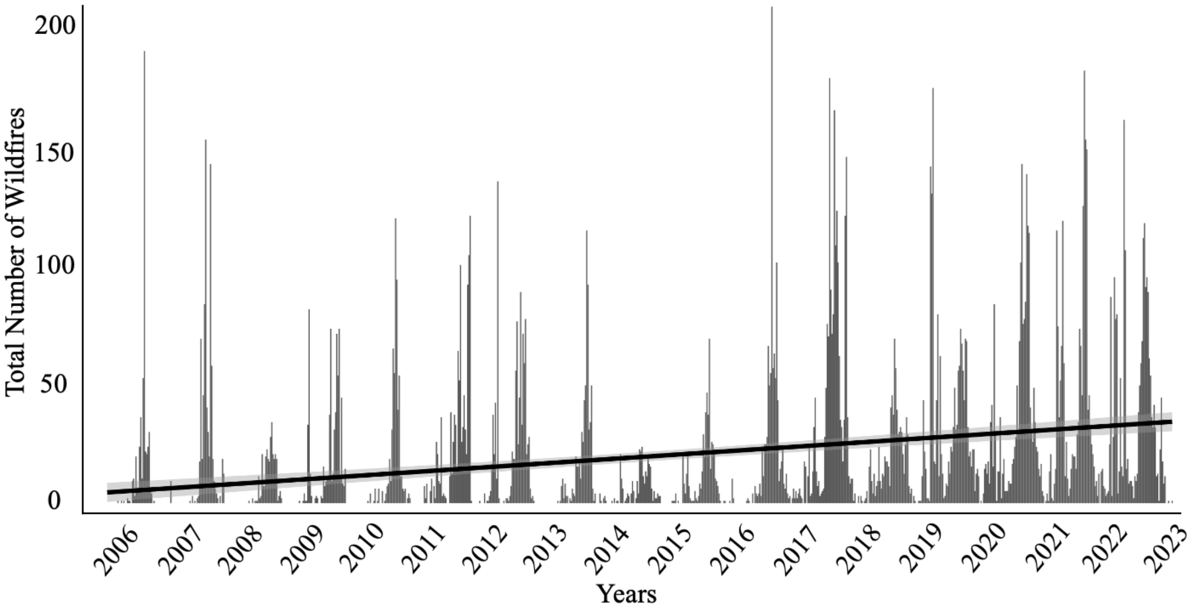
# 1. Introduction

In 2022 alone, economic damages related to weather and climate disaster events in the EU amounted to more than €50 billion, with a majority of the economic losses attributable to heatwaves, cold waves, droughts, and wildfires (European Environment Agency, 2023). Climate disaster events such as wildfires are due to rising temperatures, increasing occurrence of droughts, and agricultural practices becoming increasingly frequent and severe (Center for Climate and Energy Solutions, 2018; The European Commission, 2023). In addition to the tragic loss of lives and devastating impact on societies and local populations, wildfires have a substantial negative impact on assets such as housing, forestry, and infrastructure (Intergovernmental Panel on Climate Change, 2019). Consequently, this constitutes an interesting and important area of research. In this study, we examine the occurrence and development of wildfire severity in a selection of countries in Europe and measure if, and to what extent, this proxy for climate change has a material impact on companies within the forestry and paper and pulp (P&P) industries. Thereafter, we investigate the extent and magnitude of the stock market's responses to these events in the context of the Efficient Market Hypothesis (EMH). We use the methodology put forward by Hong, Wekai Li and Xu in the article *Climate risks and market efficiency* (2018).

**Figure 1.** Total Number of Wildfires Over Time




The figure reports the total number of wildfires per month, aggregated for all countries in our dataset during the period 2006 until 2023, based on data from the European Forest Fire Information System (EFFIS). The trend for the period is outlined in the graph.

Our sample starts from 2003, the year from which the European Forest Fire Information System (EFFIS), a European Commission established system aimed at supporting services in charge of the protection of forest fires in the EU and neighboring countries, first provides data on wildfires for European countries. EFFIS is based on the European Fire Database and comprises more than 2 million data records relating to forest fires provided by 22 European countries from 2003 until today, and utilizes satellite Earth observations as well as in-situ data for its data collection (EFFIS, 2023). During the period 2003 to 2022, the aggregated average number of yearly wildfires for the 14 countries we have selected for our research amounted to approximately 994 and the average burnt area equaled 349,314 hectares. The distribution among the analyzed companies is dispersed, where Switzerland exhibited the fewest average wildfires per year of mere 0.2 while Italy experienced the highest number of an astounding 276 yearly wildfires on average. Some countries and years stand out as particularly intensive, such as 2018 when Italy suffered a devastating wildfire season with more than 780 wildfires alone, while other years exhibited significantly less wildfire severity, such as the following year of 2019 with less than 500 wildfires for all countries combined (EFFIS, 2023). Explanatory factors to the large dispersion include geographical settings, weather variations, as well as discrepancies in global fire fighting capabilities (International Association of Wildland Fire, 2020; National Park Service, 2017).

As forest wildfires likely have a material impact on companies operating within the forestry and P&P industries and are of growing interest in terms of climate change (Wang and Lewis, 2023), we find this an interesting research area to study in more detail. As such, in this paper we study the material impact of wildfires on within-industry companies across countries and the stock market's response to these climate events in the context of current finance theory and research. More specifically, our paper aims to answer the following research questions:

i. *Does the trend in wildfire severity have a significant material impact on companies in terms of net income?*

ii. *In the aftermath of wildfire severity trends having a significant material impact on companies' net income, does the market efficiently respond to this publicly available information in accordance with the Efficient Market Hypothesis?*

Prior studies relating to climate disaster events have mainly been divided in three distinct areas of research, namely climate disaster events and the effects on asset prices, wildfires and the effects on asset prices, and climate disaster events and market response. Notable studies include the impact of natural disasters on stocks within the financial sector, the effects of wildfires on the housing market, as well as event studies measuring stock market reactions to climate disaster events. Our research builds upon and extends these studies by measuring climate disaster events' material impact on asset prices in the light of wildfire severity and the subsequent stock market reactions to these events. As such, this research advances previous findings of climate disaster events and stock market efficiency on a new strand of assets by a different proxy for climate change, opening up a new and salient area of finance and climate research.

We study the effects of wildfire severity's material impact on forestry and P&P companies and the stock market's reactions to this information during the time period 2013 to 2022, the total time period of EFFIS' publicly available wildfire severity data. Since wildfire severity is constructed through a multitude of factors such as temperature, relative humidity and weather precipitation (Natural Resources Canada, 2023), and therefore is less affected by confounding factors such as societal improvements of firefighting or general actions undertaken to mitigate the occurrence of wildfires, we find this measure to be a better proxy for changes in climate change compared to, for instance, the number of wildfires or areas burnt. As forestry and P&P companies by their inherent nature are more affected by wildfires and the related disruption in firm operations (Bousfield et al., 2023), we expect to see a higher material impact and subsequent trading activity for these companies. Furthermore, as we want to study the effects of wildfire severity on forestry and P&P companies in terms of material impact and stock market returns spanning over a longer period of time, we conduct a longitudinal study on the total time period containing publicly available data, 2003 to 2022.

Utilizing wildfire data by EFFIS, we rank countries based on their wildfire severity indices and test for trends having a significant material impact on firms within the forestry and P&P industries. Thereafter, we use intraday trading data covering the largest stock exchanges for a set of 14 countries in order to assess stock market returns in the context of market efficiency.

Our results show that countries are experiencing significantly different trends in terms of wildfire severity, where a few countries exhibit a positive trend and others strong negative trends. There is a significant forecastability of changes in forestry and P&P industry profitability based on the trends in wildfire severity. Countries with positive time trends in wildfire severity experience lower growth in profits than countries with less positive time trends. This publicly available information should in an efficient market, even though they predict future profitability within the industries, not be able to forecast future stock returns. In line with this, our results show that these rankings cannot forecast future stock returns and that the market does efficiently price in climate risk as measured by wildfire severity.

# 2. Theoretical Framework and Related Literature

In order to study the effects of wildfires in the context of market efficiency, we have drawn upon a number of studies and areas of research. Firstly, our study utilizes research covering climate disaster events and the effects on asset prices. Moreover, studies of climate disaster events and market response have been of large interest for our theoretical framework and results. Lastly, one area of research that our study naturally is closely related to includes prior studies of wildfires and the effects on asset prices. The research focusing on climate disaster events and its impact on economies and financial markets have during recent years seen an increased interest. As the climate crisis is growing ever more salient and climate disaster events are becoming more frequent, further research and studies on the topic are expected to be undertaken in the near future.

## 2.1 Climate Disaster Events and the Effects on Asset Prices

Climate disaster events have, not surprisingly, large impacts on asset prices and global capital markets. As firms are affected by climate disaster events in terms of supply chain and production disruptions, physical damage to tangible assets, and other operating performance, market participants react differently to these news.

Our study uses the methodology put forward by Hong, Wekai Li and Xu (2018), who study the impact of droughts on companies within the food industry. The authors use the Palmer Drought Severity Index (PDSI) as a proxy for climate change and models country-specific trends in droughts for 31 countries across America, Europe and Oceania. As food industries in countries suffering adverse effects of droughts (due to the reliability of water supplies) exhibit lower financial performance in terms of net income, the authors measure how food companies' cash flows are affected by these trends and whether the stock markets are efficiently pricing the risks associated with climate change. They found that there is a strong forecastability of changes in food industry profitability and stock returns, suggesting that the market is not efficient in terms of correctly pricing these climate risks.

Furthermore, Bebhe and Ndlovu (2020) study the impact of natural disasters and climate change risk on the performance of stocks within the financial sector. The authors use a Seemingly Unrelated Regression (SUR) in conjunction with an ARCH/GARCH model to predict index volatility and isolate abnormal returns for stocks listed on the Johannesburg Stock Exchange (JSE). The index used is the JSE all-share index and the period studied is 1995 to 2021. The authors find results suggesting that the occurrence of natural disasters have a negative impact on the index and, conditional on the observed above-market performance, that stocks within the financial sector experience a negative impact from the occurrence of natural disasters. Our paper builds upon partial similarities in terms of measuring the effect of natural disaster events' impact on stock indices. However, our methodology differs from the work of Bebhe and Ndlovu (2020) by instead of measuring the across-industry effects of natural disaster, we delineate our analysis to examine the impact of a specific natural disaster category on listed stocks within a certain industry and as such study the explicit impact of wildfire severity on stocks within the forestry and P&P industries.

## 2.2 Wildfires and the Effects on Asset Prices

As the negative impact following wildfires has been estimated to amount to several billions of dollars by affecting countries and economies in terms of labor market disruptions, damages to assets and infrastructure, as well as production losses (Meier et al., 2023), this is not surprisingly of large interest when studying wildfires and the effects on asset prices. Adachi and Li (2023), who study the effects of wildfire risk on property prices in South Australia, find that houses that are located in areas more prone to wildfires experience a 4.96% price discount compared to houses not located in these areas after a wildfire has occurred. The authors show that this effect is withstanding six months after a wildfire and persists up to two years after the wildfire occurrence, suggesting that wildfire risk perception is evident following a wildfire event and that wildfires have a direct effect on asset prices. This is important for our study as we examine the effect of wildfire severity on forestry and P&P company profitability, rendering the same conclusion that wildfires have a material impact on asset prices.

In a study by Wang and Lewis (2023), the authors examine the effect of wildfires and droughts on the economic value of forests and biological assets by employing parcel-data over a 17-year period in three Pacific states in the US. In addition, the authors study changes in risk perception by examining woodland prices of forests in close proximity to areas that have suffered from wildfires. While the authors' results indicate a substantial effect on asset prices, estimated by more than $6 billion in economic damages attributed from climate change, the authors suggest that most of the damages arise from changes in investors' risk perception rather than the actual economic damages per se. The finding that wildfires are suggested to have a substantial material impact on asset prices is important for our research question and framework, as we motivate the forestry and P&P industries as being the most affected industries by wildfires and wildfire severity. Furthermore, in addition to our results being much in line with those of Wang and Lewis (2023), our study partly builds upon their research and findings by proxying the impact of wildfires by wildfire severity and extends the research of wildfire severity's impact on woodland asset prices in European countries through a different set of firm fundamentals, namely forestry and P&P companies' net income.

## 2.3 Climate Disaster Events and Market Response

In their study, Pagnottoni et al. (2022) analyze the effects of natural disasters on 27 global stock market indices and find heterogeneous stock market reactions, with the most extreme reactions caused by climatological and biological disasters. Among the indices analyzed, the authors find that European indices are the ones most responsive to climate disaster events. This is of importance for our study since we mainly examine European countries and the stock market reactions relating to forestry and P&P companies within these countries. As such, the results of Pagnottoni et al. (2022) suggest that the countries examined in our study should be prone to swiftly respond to market events and in particular differences in wildfire severity.

This conclusion is further strengthened in a study conducted by McCoy and Walsh (2018), who research changes in location-specific risk perceptions to housing markets following wildfire risk. More specifically, the authors empirically model the link between wildfire occurrence and housing market dynamics by developing a framework that measures the relative price and quantity dynamics in the context of salience shocks in communities facing a high and low risk of wildfires, respectively. In that way, the study measures climate-driven increases in the risk of wildfires as well as social dynamics that capture the market's response to climate disaster events in the form of wildfires. Here, the authors find evidence for immediate short-term price shocks in the year following a wildfire to housing situated in the high risk areas, which is not evident for housing situated in low risk areas. Importantly, the results show that the immediate shocks are only temporary during the initial two to three years following a wildfire, illustrating the large effects of market response and changes in risk perception in addition to measurable economic damages following wildfires. This is closely related to our study as we examine market efficiency in the context of wildfire severity affecting companies' financial fundamentals, which by its nature to a large extent is driven by saliency and investor emotions.

### 2.4 Contribution

To our present knowledge, no paper aimed at quantifying the material impact of wildfires on listed companies within the forestry and P&P industries and subsequently testing the market's response to those events have yet been published. Therefore, this study contributes to the existing literature in several ways. Utilizing the framework of Hong, Wekai Li and Xu (2018), we measure the trend of climate events across a number of selected countries. In contrast to Hong, Wekai Li and Xu (2018), however, we study the trends of climate disaster events in the form of wildfire severity and its effects on the forestry and P&P industries. Thus, our study extends the existing research of market efficiency related to climate disaster events into wildfires and the forestry and P&P industries. Moreover, in much the same way as Bebhe and Ndlovu (2020) measure across-industry effects of natural disasters, our study contributes to this by delineating the analysis to specific natural disaster events in the form of wildfire severity on listed stocks within the forestry and P&P industries rather than indices. Lastly, our research contributes to the existing literature on market response to information surrounding wildfires, such as the study by McCoy and Walsh (2018), by examining short-term stock market responses to wildfire severity trends for publicly traded forestry and P&P companies. Through our contributions, we hope to elucidate a new area of research for future scholars to build upon.

## 3. Hypotheses

*i. We expect that negative trends in wildfire severity will have a negative material impact on the forestry and P&P industries in terms of net income.*

Hong, Wekai Li and Xu (2018) show that a climate related drought index has a significantly negative impact on food industry profitability, where food companies situated in countries with a negative trend in drought experience a significantly negative effect in terms of net revenue. We expect to see a similar result in our study, where forestry and P&P companies experience a significant negative material impact following a higher wildfire severity trend as seen by the wildfire severity rating.

ii. *We hypothesize that the market is efficiently pricing the risks associated with wildfire severity on companies' cash flows within the forestry and P&P industries.*

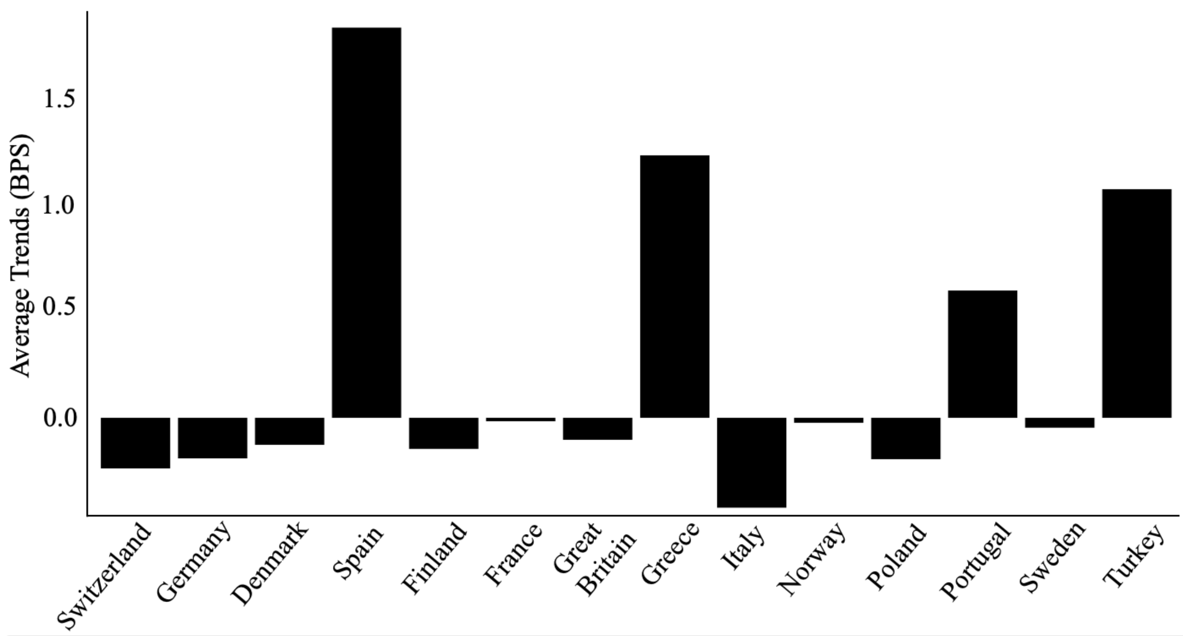
In Hong, Wekai Li and Xu's (2018) study, the authors find that the market does not efficiently price in risks associated with droughts for companies within the food industry even after a forecastability has been established between the drought index and the food industry profitability, providing evidence for the occurrence of inefficiencies within the stock market. However, the authors thereafter make the same analysis and controls for additional sectors beyond the food industry, such as utilities and basic resources, but conclude that no such findings can be seen. Since our research setting does not differ substantially in terms of dependent (the change in forestry and P&P industry profitability) and independent (wildfire severity trend) variables, we hypothesize that the market is efficiently pricing the risks associated with wildfire trends on companies' cash flows within the forestry and P&P industries.

# 4. Data

## 4.1 Wildfire Trend Measures

In order to measure trends in wildfires, we have used data from the European Forest Fire Information System, EFFIS. EFFIS is a European Commission established system aimed at supporting services in charge of the protection of forests against wildfires in the EU and neighboring countries and provides a number of statistics related to wildfires such as the number of wildfires, the areas burnt in hectares (ha), emissions following wildfires, thermal anomalies, as well as a wildfire severity rating. The majority of the data published is in a weekly format, making each measurement variable contain 52 observations per year in total.

**Figure 2.** Average Wildfire Severity Trend Per Country

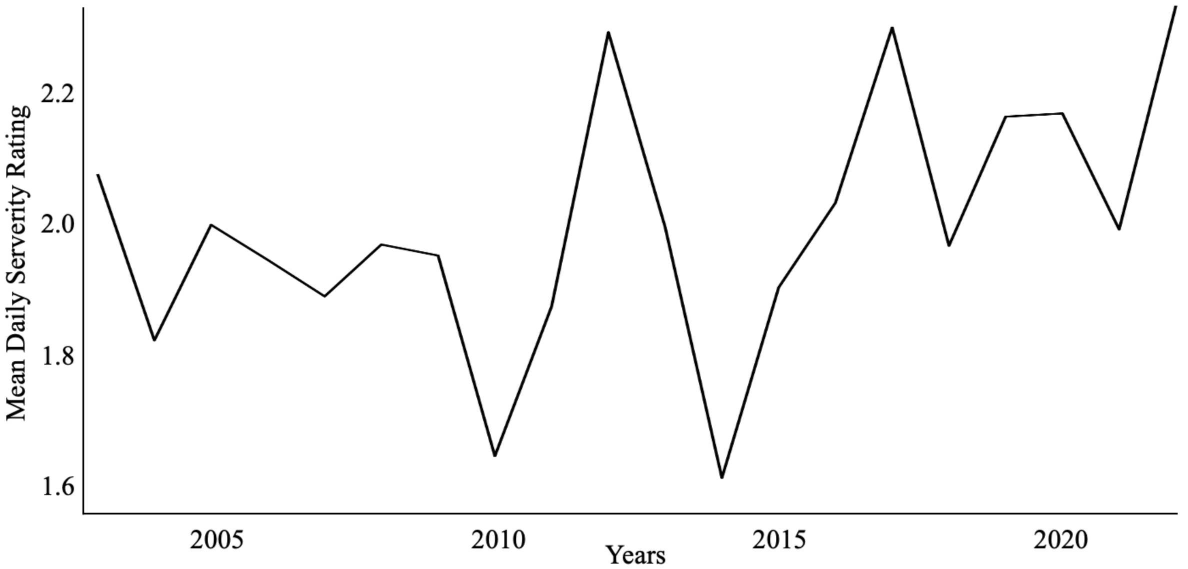



The figure depicts the average trend values (in basis points) in wildfire severity per each country included in our dataset. The trend values are based on data from the European Forest Fire Information System (EFFIS).

We follow the methodology of Hong, Wekai Li and Xu (2018) in their article *Market Efficiency and Climate Risks*, although while they study the impact of droughts on stocks within the food industry by utilizing a drought severity index, our study investigates the impact of wildfire severity through a weekly wildfire severity rating. The wildfire severity rating is part of the Canadian Forest Fire Weather Index (FWI) System, which incorporates weather data in order to provide a numerical rating of the risk of wildland fires and consists of six components, namely Fine Fuel Moisture Code (FFMC), Duff Moisture Code (DMC), Drought Code (DC), Initial Spread Index (ISI), Buildup Index (BUI), and lastly Fire Weather Index (FWI). An additional component of the FWI system, the Daily Severity Rating (DSR), is based on the FWI system but more accurately takes into account the efforts associated with fire suppression. Since our research question aims to explore the risk of wildfires having a material impact on forestry and P&P companies, and not the actual number of wildfires or the amount of areas burnt per se, we are using the wildfire severity rating DSR as a better proxy for the risk of wildfires. By utilizing wildfire severity rating as a proxy for climate change, our variable is not impacted by confounding factors such as overall societal improvements in firefighting capabilities or general actions undertaken to mitigate the occurrence of wildfires, which would have been the case if the actual number of wildfires or amount of areas burnt would have been used as proxies for climate change.

As such, we have used the EFFIS Weekly Severity Rating (which is an average of the DSR) as a proxy for wildfire severity over time across the analyzed countries. In total, the EFFIS Weekly Severity Rating consists of 31 countries across Europe, America, and Oceania. After filtering out the countries that we could not obtain annual market return for as well as companies that at present only had one or no listed companies within the forestry and P&P industries, we are left with 14 countries in our dataset (a full list of all countries included is available in Table 15 in the Appendix). This filtering, which limits us to less than half the amount of countries used by Hong, Wekai Li and Xu (2018), makes each country have a larger impact on the data and could lead to a reduced generalizability. There is also a risk of selection bias as our market returns were only available for European countries and Turkey, which again might reduce the external validity. As we are interested in the wildfire severity over the years 2003 to 2022, we constructed a web-extracting script in Java using the EFFIS API in order to download all weekly data from EFFIS' website, making our final wildfire trend data consisting of approximately 25,000 data points in total. In an ideal setting, our wildfire trend measures would be based on a dataset spanning more than 20 years, which is the total wildfire severity data publicly available at EFFIS as of now, as this short time period could make our current trends less robust and be more prone to short-term fluctuations. This would enable us to assess the effects of trends over a longer period of time, which likely is of importance since climate change progressively affects the wildfire severity rating, and would create more robust trends that measure long-term movements in wildfire severity rating rather than potential short-term fluctuations.

**Figure 3.** Yearly Mean of Daily Severity Rating Across All Countries




The figure displays the yearly mean of wildfire severity, aggregated for all countries included in our dataset. The Daily Severity Rating is based on data from the European Forest Fire Information System (EFFIS).

## 4.2 Forestry and P&P Companies

Since our study investigates the material impact of wildfire severity on companies in terms of net income, we have chosen the forestry and P&P industries as suitable sectors to measure within-industry firm material impact since these industries have been shown to be the most affected in terms of financials following wildfires (Wang and Lewis, 2023). Moreover, as Hong, Wekai Li and Xu (2018) find that the next most affected industry following climate disaster events as measured by droughts is utilities, we believe that the forestry and P&P industries are closely linked in terms of fundamentals and similarities in firm assets. Therefore, we also include placebo tests for the utilities and healthcare industries.

In order to assess the material impact of wildfire severity trends on companies within the forestry and P&P industries, we have used financial data provided by Compustat for all forestry and P&P companies listed within the countries in our dataset. The data is based on yearly financial statements published by the companies spanning from 2013 to 2022, and is retrieved from the Wharton Research Data Services (WRDS, 2023). To measure stock returns for forestry and P&P companies within the analyzed countries, we have used monthly stock return data for the period 2013 to 2022 from Compustat (WRDS, 2023). By using the North American Industry Classification System (NAICS) coding structure, which is a six-digit hierarchical classification method used to classify companies within different industries based on their operations (United States Census Bureau, 2023), we have filtered out companies belonging to the groups 321 (forestry) and 322 (P&P). Since some companies are listed at multiple exchanges we then need to filter out any duplicates, which we do by using their IID, calculating the average trading volume of each stock's separate IID, and lastly keeping those with the highest trading volume due to the notion that a higher liquidity better represents the market's valuation of the stock. The location of each company's headquarters determines which country a stock belongs to.

After having selected all listed forestry and P&P companies within the relevant countries, we are left with a total of 114 companies. The dataset includes both live and dead stock, making our data free of any survivorship bias. Lastly, we have utilized data from the Kenneth French website in order to calculate the CAPM and Fama-French three-factor models. We chose to use the European Markets Factors and Returns 3 Factors, which contain the size factor (Small Minus Big), the value factor (High Minus Low), and the market return factor (Market Return Minus Risk-Free Rate), as that best represents the countries in our data. The Small Minus Big (SML) factor accounts for historical tendencies of large-cap stocks outperforming small-cap stocks in terms of absolute returns, the High Minus Low (HML) factor captures historical outperformance of high book-to-market stocks compared to low book-to-market stocks, and the Market (Mkt-Rf) factor takes into account the excess return of the market index minus the risk-free rate (French, 2023). The Mkt-Rf factor contains all stocks for which Fama-French has market equity data (a full list of the included countries is available in the Appendix). In the ideal scenario we would have a higher total number of countries and especially more firms per country. Unfortunately, we cannot control the number of firms per country, making the available data limiting us to these countries which will partly weaken our results. However, the relative homogeneity of countries could also be a strength.

**Table 1.** Summary Statistics by Country

| Country | Average Number of Stocks | Mean Firm Size |
|---|---|---|
| Poland | 14 | 360 |
| Turkey | 14 | 447 |
| Sweden | 13 | 27339 |
| France | 8 | 378 |
| United Kingdom | 8 | 1710 |
| Finland | 7 | 5544 |
| Germany | 6 | 166 |
| Portugal | 5 | 1896 |
| Spain | 4 | 794 |
| Italy | 4 | 174 |
| Switzerland | 3 | 1437 |
| Greece | 3 | 59 |
| Norway | 3 | 6180 |
| Denmark | 2 | 1109 |

The table displays summary statistics for the countries included in our regressions, the average number of forestry and P&P listed stocks within each country, and the mean firm size (in millions). The mean firm size is displayed in each country's domestic currency.

## 4.3 Variables

### 4.3.1 Dependent Variables

#### *4.3.1.1 Future Forestry and P&P Return*

Following the construction of variables as posited by Hong, Wekai Li and Xu (2018), we are analyzing the 12-month future forestry and P&P industry return, $FPPRET12$ in time $t + 1$, as one of our dependent variables. The variable is calculated as the absolute value-weighted return $R$ divided by the market cap for all companies within each country $i$ during each future 12-month period $t + 1$, where the market cap is calculated by taking the closing share price

$CSP$ each month, denoted 1, 2 and so forth until month 12, multiplied by the number of shares outstanding $SO$ in the same year for each firm $f$. Since the shares outstanding are based on each firm's year-end financial report, the value does not differ between the months and is therefore constant during each year. The market cap is then multiplied by the monthly return, $R$, again denoted 1, 2 and so on until month 12, each month to create a value-weighted return. We then sum the value-weighted returns and market caps of all firms per country and take the sum of weighted return divided by the sum of market cap to get the monthly value-weighted return per country. Lastly, we use the formula for compounding returns to achieve the annual compounded return and lag the value 12 months in order to arrive at our $FPPRET12$ variable:

$$FPPRET12_{i,t+1} = \left(1+\frac{\sum_i\left(CSP_{f,1,t+1}\times SO_{f,t+1}\times R_{f,1,t+1}\right)}{\sum_i\left(CSP_{f,1,t+1}\times SO_{f,t+1}\right)}\right)\times\left(1+\frac{\sum_i\left(CSP_{f,2,t+1}\times SO_{f,t+1}\times R_{f,2,t+1}\right)}{\sum_i\left(CSP_{f,2,t+1}\times SO_{f,t+1}\right)}\right) \cdots \left(1+\frac{\sum_i\left(CSP_{f,12,t+1}\times SO_{f,t+1}\times R_{f,12,t+1}\right)}{\sum_i\left(CSP_{f,12,t+1}\times SO_{f,t+1}\right)}\right)-1 \quad \text{Eq. 1}$$

#### *4.3.1.2 Change in Forestry and P&P Industry Profitability*

Our next dependent variable, the change in forestry and P&P industry profitability, $CP$, is calculated as the percentage change in forestry and P&P industry profitability from year $t$ to $t+1$, where $NI$ is the forestry and P&P industry-level net income and $A$ is the forestry and P&P industry-level book assets based on each company's end-year financial report. The net income and total assets at the industry level for the forestry and P&P sectors are calculated by summing up the individual net income and book assets of the firms operating within these industries:

$$CP_{t+1} = \frac{NI_{t+1}}{TA_{t+1}} - \frac{NI_t}{TA_t} \quad \text{Eq. 2}$$

### 4.3.2 Independent Variables

#### *4.3.2.1 Lagged Forestry and P&P Return and Market Return*

Consistent with the article by Hong, Wekai Li and Xu (2018), we perform a regression analysis using the lagged forestry and P&P return and the lagged market return as two of our independent variables. The lagged market return, $MRET12$ in time $t-1$, is simply the lagged market return in percentage per year for each country. The lagged forestry and P&P return, $FPPRET12$ in time $t-1$, is calculated as the absolute value-weighted return $R$ and market cap for all companies within each country during each lagged 12-month period $t-1$, where the market cap is calculated by multiplying all companys' year-end closing stock price $CSP$ with their amount of shares outstanding $SO$ in time $t-1$. Thereafter, we have compounded the monthly returns to yearly returns by using the formula for compounding returns:

$$FPPRET12_{i,t} = \left(1 + \frac{\sum_i^N \left(CSP_{i,f,1,t} \times SO_{i,f,t} \times R_{i,f,1,t}\right)}{\sum_i^N \left(CSP_{i,f,1,t} \times SO_{i,f,t}\right)}\right) \times \left(1 + \frac{\sum_i^N \left(CSP_{i,f,2,t} \times SO_{i,f,t} \times R_{i,f,2,t}\right)}{\sum_i^N \left(CSP_{i,f,2,t} \times SO_{i,f,t}\right)}\right) \cdots \left(1 + \frac{\sum_i^N \left(CSP_{i,f,12,t} \times SO_{i,f,t} \times R_{i,f,12,t}\right)}{\sum_i^N \left(CSP_{i,f,12,t} \times SO_{i,f,t}\right)}\right) - 1 \qquad \text{Eq. 3}$$

#### *4.3.2.2 Forestry and P&P Industry Price-to-Book*

Similar to Hong, Wekai Li and Xu (2018), we calculate the forestry and P&P industry price-to-book ratio, $FPPPB$, in time $t$ by dividing the market cap with the book value of equity for all forestry and P&P companies within each country, where the market cap is calculated by multiplying each company's year-end closing stock price $CSP$ with the amount of shares outstanding $SO$ in time $t$, and the book value of equity is calculated by subtracting total assets $TA$ with total liabilities $TL$ in time $t$. We have thereafter taken the logarithm of this ratio:

$$FPPPB_t = \log\left(\frac{(CSP_t \times SO_t)}{(TA_t - TL_t)}\right) \qquad \text{Eq. 4}$$

#### *4.3.2.3 Trend Quintile 5 and Trend Quintile 5 (2012)*

The next independent variables we construct are the yearly trends for Quintile 5, $TrendQuintile5$, and the trend for Quintile 5 from the beginning of the year 2012, $TrendQuintile5\_2012$. $TrendQuintile5$ is dummy variables taking the value 1 for countries belonging to Quintile 5 (the countries suffering the highest wildfire severity rating) at the end of December each year, and the value 0 otherwise. Similarly, $TrendQuintile5\_2012$ is a dummy variable taking the value 1 for countries belonging to Quintile 5 at the end of December 2012, and the value 0 otherwise.

#### *4.3.2.4 Inflation Rate and Dividend/Price Ratio*

In much the same way as Hong, Wekai Li and Xu (2018), we construct the inflation rate as well as the dividend/price ratio for each country during the data period. Inflation rate, $INF12$, is the lagged country-specific inflation rate per year, as published by the World Bank year-end (World Bank, 2023). The dividend/price ratio, $DP$, is the defined as the market return including dividend, $MRETID$, minus the market return excluding dividend, $MRETED$, expressed as a fraction. The dividend/price ratio and the market return is based on data from WRDS (WRDS, 2023).

**Table 2.** Summary Statistics of Variables

| Variable | Mean | Median | SD | Min | Max | N (Non-missing) | n (Missing) |
|---|---|---|---|---|---|---|---|
| CP | 1.06 | 0.71 | 6.27 | -37.67 | 29.12 | 128 | 12 |
| FPPRET12 | 21.21 | 17.93 | 44.11 | -64.19 | 358.59 | 126 | 14 |
| MRET12 | 6.99 | 8.00 | 17.47 | -45.81 | 108.58 | 139 | 1 |
| FPPPB | 0.23 | 0.20 | 0.48 | -1.10 | 1.56 | 140 | 0 |
| DP | 3.36 | 3.28 | 0.95 | 1.02 | 6.43 | 140 | 0 |
| INF12 | 2.78 | 1.11 | 6.93 | -1.74 | 72.31 | 140 | 0 |
| Trend | 0.34 | 0.06 | 0.85 | -1.10 | 3.94 | 140 | 0 |

The table reports the mean, median, standard deviation (SD), minimum value, maximum value, N (Non-missing) and n (Missing) for the variables forestry and P&P industry profitability $CP$, 12-month future forestry and P&P industry $FPPRET12$, 12-month lagged market return $MRET12$, forestry and P&P price-to-book ratio $FPPPB$, dividend/price ratio $DP$, 12-month lagged inflation rate $INF12$, and the end-year wildfire severity trend value $Trend$.

**Table 3.** Correlation Matrix of Independent Variables

| | CP | FPPRET12 | MRET12 | FPPPB | DP | INF12 | Trend |
|---|---|---|---|---|---|---|---|
| CP | 1 | | | | | | |
| FPPRET12 | -0.011 | 1 | | | | | |
| MRET12 | 0.147 | 0.365 | 1 | | | | |
| FPPPB | -0.02 | 0.099 | 0.057 | 1 | | | |
| DP | 0.074 | -0.049 | -0.078 | 0.002 | 1 | | |
| INF12 | 0.181 | 0.146 | 0.197 | 0.069 | 0.05 | 1 | |
| Trend | 0.049 | 0.09 | -0.044 | -0.098 | 0.048 | 0.323 | 1 |

The table displays the correlation between the independent variables forestry and P&P industry profitability $CP$, 12-month future forestry and P&P industry $FPPRET12$, 12-month lagged market return $MRET12$, forestry and P&P price-to-book ratio $FPPPB$, dividend/price ratio $DP$, 12-month lagged inflation rate $INF12$, and the end-year wildfire severity trend value $Trend$.

As can be seen in the correlation matrix, our independent variables exhibit low correlations with each other and thus suggest no concerns related to multicollinearity. The lack of correlation improves the interpretability and fortifies the precision of our statistical model by using unbiased parameter estimations. In that way, each variable contributes uniquely to our model without being confounded by collinearity and allows us to better employ the variables across our different regressions.

**Table 4.** Variable Definitions

| Variable | Definition |
|---|---|
| CSP | Closing Share Price |
| SO | Shares Outstanding |
| R | Monthly Return |
| TA | Total Assets |
| TL | Total Liabilities |
| NI | Aggregated Net Income for the forestry and P&P industries |
| CP | (Net Income (t+1) / Total Assets (t+1)) - (Net Income (t) / Total Assets (t)) |
| FPPRET12 | 12-month lagged forestry and P&P return |
| MRET12 | 12-month lagged market return |
| FPPPB | Log((Closing Share Price * Outstanding Shares) / (Total Assets - Total Liabilities)) |
| DP | Dividend / Price Ratio (Dividend Yield) |
| INF12 | 12-month lagged inflation rate |
| Trend | End of year wildfire severity trend value |
| TrendQuintile5 | Dummy variable equal to 1 for countries belonging to trend quintile 5 in December each year |
| TrendQuintile5_2012 | Dummy variable equal to 1 for countries belonging to trend quintile 5 in December 2012 |

The table reports the definitions for our variables.

# 5. Methodology

## 5.1 Longitudinal Study

In order to answer our research questions, we follow the methodology outlined by Hong, Wekai Li and Xu in the article *Climate risks and market efficiency* (2018). As such, our study is a longitudinal study that aims to explore market efficiency in the context of wildfire severity having a material impact on companies within the forestry and P&P industries. A longitudinal study is a research method that measures repeated observations over a longer period of time, so-called longitudinal or panel data, and has been used for research purposes for hundreds of years. Therefore, it is an appropriate method to measure cause-and-effect relationships across time and is particularly suitable for our research question as we aim to explore the effects of wildfire severity on companies' profitability in terms of net income, which by its nature have a time-dependent effect by gradually, over a longer period of time, affecting companies and their operations (Giang et al., 2021).

## 5.2 OLS-Regression

Utilizing Hong, Wekai Li and Xu's (2018) methodology, we measure trends in wildfires by using the EFFIS Weekly Severity Rating in order to measure whether or not investors are correctly pricing these risks. To start with, we use their method of sorting out suspicious returns by setting returns to missing for stocks that have risen 300% or more within a month and then declining by 50% or more the following month. Further, we treat returns above 1000% as missing. We also winsorize returns at the 1st and 99th percentile to reduce the impact of outliers on our results (McLean et al., 2009). While Hong, Wekai Li and Xu (2018) perform an autoregressive (AR) model for drought augmented with a deterministic time trend $t$, the authors also tested several different models which gave approximately the same results. Therefore, we initially use an ordinary least square (OLS) model that regress the fire risk, $Fire\ Risk$, on time, $t$, up until the end of 2012, where β is the trend in wildfire severity, α is the intercept, ε denotes the error term, and $i$ denotes the country:

$$Fire\ Risk_{i,t} = \alpha_i + \beta_i t + \varepsilon_{i,t} \quad \text{Reg. 1}$$

Thereafter, we created a more advanced, iterative version that calculates monthly trend values for each month from January 2013 until December 2022 by utilizing the same regression as outline by Equation 5, where the trend is based on all data up until month $t$. The reason for running this OLS-regression in conjunction with the iterative model is to observe whether the trends are stable over time and not just displaying temporary variation. Based on our OLS-regression results, we segmented the data into quintile groups based on their trend values. Quintile 1 is composed of countries with the least deterioration in wildfire severity conditions over the study period. Conversely, Quintile 5 consists of countries that experience the most severe worsening in wildfire severity.

## 5.3 Statistical T-Tests

Like Hong, Wekai Li and Xu (2018), we utilize Welch's two sample t-test for unequal variances, which is used to test whether or not two populations have equal mean. In our study, we test if there is a statistically significant difference in wildfire severity trends between countries with the most severe worsening of wildfire severity conditions and those with the least deterioration, as well as if there is a difference between the change in profitability for forestry and P&P companies in Quintile 5 and Quintile 1, respectively. We test this by calculating the test statistic and analyzing the corresponding p-values as given by the calculations outlined by Newbold et al. (2022), where $\bar{x}$ and $\bar{y}$ are the sample means, $s$ is the sample variance, and $n$ is the sample size:

$$t = \frac{\bar{x} - \bar{y}}{\sqrt{\frac{s_x^2}{n_x} + \frac{s_y^2}{n_y}}} \quad \text{Eq. 6}$$

Firstly, we test the hypothesis that the mean wildfire severity trend in Quintile 1 is significantly less than in Quintile 5, implying a lesser deterioration in wildfire severity conditions in Quintile 1 compared to Quintile 5. This hypothesis aligns with our research objective to understand the disparities in wildfire severity progression across different global regions. We perform the test as a one-sided t-test with the following null and alternative hypothesis for average wildfire severity trend:

$$H_0 : Q1 - Q5 \geq 0$$
$$H_1 : Q1 - Q5 < 0$$

Next, we perform a two-sided t-test to test the hypothesis that there is a significant difference between the change in profitability for forestry and P&P companies in Quintile 5 and Quintile 1 for year $t$ to $t + 1$, $t$ to $t + 2$, and lastly $t$ to $t + 3$, rendering three hypothesis and alternative hypothesis for each period:

$$H_0 : Q1 - Q5 = 0$$
$$H_1 : Q1 - Q5 \neq 0$$

## 5.4 Portfolio Sorts

Consistent with Hong Wekai Li and Xu (2018), we follow Fama and French (2000) in order to measure the change in forestry and P&P profitability by comparing the profitability of portfolios and then sorting the quintile portfolios based on the trends in wildfire severity. As such, at the end of each year $t$, we sort countries into quintile portfolios based on their wildfire severity trends using data up to year $t$ and hold the portfolios for one, two and three years, respectively. Thereafter, we report the changes in percentage. Quintile 5 contains firms in countries with the worst wildfire severity trend and Quintile 1 contains firms in countries with the best wildfire severity trend. The sample period used is 2013 until 2022. To calculate the change in profitability for the quintile portfolios for two and three years, we use Equation 2.

We are interested in examining if markets are efficiently responding to information regarding long-term trends in wildfire severity. Our previously calculated monthly value-weighted portfolio returns are used in combination with the Fama-French factors from Kenneth-French to calculate CAPM alphas and Fama-French three-factor model alphas on overlapping portfolios that we construct following Jegadeesh and Titman (1993). This is done to investigate whether these quintile portfolios have significantly different returns as well as smoothing out short-term stock volatility and potential noise. At the end of month $t$, we sort the forestry and P&P-industry portfolios across all countries into quintiles based on their wildfire severity trends up to month $t$. Returns for each quintile portfolio is the equal-weighted average returns of all countries within each portfolio. Each portfolio is held for 12, 24, and 36 months, respectively. For each quintile portfolio at month $t$, we have 12 (24, 36) portfolios formed. Returns for the 12 (24, 36) portfolios are then equally-weighted in order to receive the average return for each quintile portfolio for month $t$. The oldest portfolio is removed and replaced with a new portfolio every month. Because of the method of portfolio creation the portfolio returns for 12-month holdings have data for 2014 to 2022, 24-month holdings 2015 to 2022 and lastly the 36-month holdings 2016 to 2022. We construct four different portfolios, namely one for Quintile 1, one for Quintile 2-4, one for Quintile 5, and lastly one for Quintile 1 minus Quintile 5, which is a long-minus-short portfolio. Consequently, our study employs linear regression models to analyze the returns of the portfolios categorized by wildfire severity.

More specifically, we conduct three separate regressions for each quintile with portfolio holdings of 12, 24, and 36 months, respectively. Firstly, we regress the excess return mode, which is a basic model considering only the intercept and represents the excess returns of the portfolios. Secondly, we regress the Capital Asset Pricing Model (CAPM), which includes the market return to account for market-related variances in portfolio returns. Lastly, we regress on an extension of the CAPM, the Fama-French three-factor model, which incorporates the three factors market return $MKTRF$, size $SMB$, and value $HML$, providing a more comprehensive view of the returns influenced by different market dynamics. We also report the t-values for our long/short portfolio, consisting of Quintile 1 minus Quintile 5, which is our primary portfolio of interest. The value we are interested in is the alpha (intercept) for all portfolios, which is the only value we report from each regression where $i$ denotes the quintile portfolios:

$$Portfolio\ Return_i = \alpha_i + \varepsilon_i \qquad \text{Reg. 2}$$

$$Portfolio\ Return_i = \alpha_i + \beta_1 MKTRF_i + \varepsilon_i \qquad \text{Reg. 3}$$

$$Portfolio\ Return_i = \alpha_i + \beta_1 MKTRF_i + \beta_2 SMB_i + \beta_3 HML_i + \varepsilon_i \qquad \text{Reg. 4}$$

## 5.5 Cross-Country Regression

Following the methodology of Hong, Wekai Li and Xu (2018), we run cross-country regressions in order to check whether or not a company belonging to the worst countries in terms of wildfire trend has a material impact on firm profitability. Based on our regression results of trends, Regression 1, we create a dummy variable called $TrendQuintile5$ taking the value 1 for countries with the worst wildfire severity trend and 0 otherwise. A similar dummy variable, $TrendQuintile5\_2012$, is created with the same sorting although only based on the trend up until the end of 2012. Thereafter, we run our regression on the dependent variable, the change in forestry and P&P industry profitability, denoted $CP$. As outlined in the data section, we conduct regressions with the following independent variables:

| | |
|---|---|
| $TrendQuintile5$ | = Dummy variable taking the value 1 for the countries with the worst wildfire severity trend and 0 otherwise |
| $TrendQuintile5\_2012$ | = Dummy variable taking the value 1 for countries with the worst wildfire severity trend at the end of 2012 and 0 otherwise |
| $FPPPB$ | = Logarithm of the Price-to-Book ratio for the forestry and P&P Industries |
| $FPPRET12$ | = 12-month lagged forestry and P&P return |
| $DP$ | = Dividend yield |
| $MRET12$ | = 12-month lagged market return |
| $INF12$ | = 12-month lagged inflation rate |

The cross-sectional regression of our dependent variable $CP$ is performed as a Fama-Macbeth (1973) regression that controls for country and industry characteristics in order to check for robustness. Each year $t$, we run a cross-sectional regression with the one-year future change in profitability as our dependent variable. Our first regression uses only $TrendQuintile5$ as the independent variable to check if there is a correlation with the future industry profitability. Secondly, we add two control variables, $FPPPB$ and $FPPRET12$, to check if the potential correlation can be explained by these variables. Lastly, we add an additional three control variables, $DP$, $MRET12$, and $INF12$, to check whether our potential correlation is robust to the inclusion of our control variables. To control for potential autocorrelation and heteroskedasticity, our standard errors are Newey-West (1987) adjusted with a lag of six periods. Thereafter, the regressions are repeated using $TrendQuintile5\_2012$ as our primary independent variable to investigate if our trend rankings are long-term trends and not temporary fluctuations:

$$CP_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 5}$$

$$CP_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{i,t} + \beta_2 FPPPB_{i,t} + \beta_2 FPPRET12_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 6}$$

$$\begin{gathered} CP_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{i,t} + \beta_2 FPPPB_{i,t} + \beta_3 FPPRET12_{i,t} \\ + \beta_4 DP_{i,t} + \beta_5 MRET_{i,t} + \beta_6 INF12_{i,t} + \varepsilon_{i,t+1} \end{gathered} \qquad \text{Reg. 7}$$

$$CP_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend\_2012_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 8}$$

$$CP_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend\_2012_{i,t} + \beta_2 FPPPB_{i,t} + \beta_2 FPPRET12_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 9}$$

$$\begin{gathered} CP_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{2012_{i,t}} + \beta_2 FPPPB_{i,t} + \beta_3 FPPRET12_{i,t} \\ + \beta_4 DP_{i,t} + \beta_5 MRET_{i,t} + \beta_6 INF12_{i,t} + \varepsilon_{i,t+1} \end{gathered} \qquad \text{Reg. 10}$$

Next, in order to examine if there is a correlation between $TrendQuintile5$ and future stock returns, we change our dependent variable to the 12-month future forestry and P&P industry returns, $FPPRET12$, for country $i$ in time $t+1$. The first regression has no control variables. The second regression controls for two variables, $FPPPB$ and $FPPRET12$. The third regression checks whether our results are robust for the inclusion of three additional control variables, $DP$, $MRET12$, and $INF12$.

$$FFPPRET12_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 11}$$

$$FFPPRET12_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{i,t} + \beta_2 FPPPB_{i,t} + \beta_2 FPPRET12_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 12}$$

$$\begin{gathered} FFPPRET12_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{i,t} + \beta_2 FPPPB_{i,t} + \beta_3 FPPRET12_{i,t} \\ + \beta_4 DP_{i,t} + \beta_5 MRET_{i,t} + \beta_6 INF12_{i,t} + \varepsilon_{i,t+1} \end{gathered} \qquad \text{Reg. 13}$$

$$FFPPRET12_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend\_2012_{i,t} + \varepsilon_{i,t+1} \qquad \text{Reg. 14}$$

$$FFPPRET12_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{2012_{i,t}} + \beta_2 FPPPB_{i,t} + \beta_2 FPPRET12_{i,t} + \varepsilon_{i,t+1} \quad \text{Reg. 15}$$

$$FFPPRET12_{i,t+1} = \alpha_{i,t} + \beta_1 LowTrend_{2012_{i,t}} + \beta_2 FPPPB_{i,t} + \beta_3 FPPRET12_{i,t} + \beta_4 DP_{i,t} + \beta_5 MRET_{i,t} + \beta_6 INF12_{i,t} + \varepsilon_{i,t+1} \quad \text{Reg. 16}$$

### 5.6 Placebo Tests and Correlation Matrix

Additionally, we conduct a robustness check by undertaking a permutation test where we randomize our $TrendQuintile5$ variable and reiterate our regressions 500 times. Thereafter, we plot the distribution of the estimate of our main outcome variable Quintile 5 and compare this to our baseline regression in order to examine if our coefficients fall in the middle or in the tails of the random distribution. As such, we test if our findings are a result of random noise or actual effect. Moreover, we conduct a placebo test that uses non-forestry or P&P industries and calculates excess return, CAPM alpha and Fama-French three-factor alphas for returns to portfolios sorted on wildfire severity trends. We re-do the same analysis as previously done in our portfolio sorts but instead filter for companies belonging to NAICS code 22 and 62, which represent healthcare and utilities, respectively. The results of these tests can be found in the Appendix. Finally, in order to control for potential multicollinearity issues and identify potential dependencies between our independent variables, we construct a correlation matrix to examine the correlation between the independent variables.

## 6. Empirical Results

**Table 5.** Summary Statistics of Fire Severity Trend Estimates Over Time, Country by Country

| Country | Average Intercept | Average Intercept T-Statistic | Average Trend | Average Trend T-Statistic |
|---|---|---|---|---|
| Spain | 3.33 | 0.82 | 1.71 | 0.55 |
| Greece | 2.52 | 0.84 | 1.15 | 0.45 |
| Turkey | 4.68 | 0.95 | 1.00 | 0.32 |
| Portugal | 3.78 | 1.04 | 0.56 | 0.25 |
| France | 1.23 | 1.20 | -0.02 | 0.13 |
| Norway | 0.12 | 1.03 | -0.02 | -0.19 |
| Sweden | 0.33 | 0.95 | -0.04 | -0.09 |
| United Kingdom | 0.40 | 1.62 | -0.10 | -0.51 |
| Denmark | 0.56 | 1.20 | -0.12 | -0.32 |
| Finland | 0.45 | 1.25 | -0.14 | -0.48 |
| Germany | 0.83 | 1.08 | -0.18 | -0.17 |
| Poland | 1.06 | 1.10 | -0.18 | -0.11 |
| Switzerland | 0.47 | 1.78 | -0.22 | -1.10 |
| Italy | 2.79 | 1.43 | -0.39 | -0.30 |

The table displays the summary statistics for fire severity trend estimates over time on a rolling basis. For each month $t$, we use our wildfire severity data for a country from 2003 up to month $t$ to estimate our model during the sample period 2003 to 2022. We report the average intercept, average t-statistic intercept, average wildfire severity trend, and average t-statistic trend, where the intercepts and trends are Newey-West (1987) adjusted.

Table 5 reports the summary statistics for our iterative regressions for the estimation of wildfire trend values per country. For each country, the constants, trend estimates, and t-statistics shown are the averages of the estimates and t-statistics over all months from the rolling regressions.

**Table 6.** T-Test for Difference Between Quintile 1 and Quintile 5

| Statistic | Value |
|---|---|
| **T-Statistic** | -31.081474 |
| **Degrees of Freedom** | 293.417021 |
| **P-Value** | 0.000000 |
| **Confidence Interval Lower** | -Inf |
| **Confidence Interval Upper** | -1.927454 |

The table reports the result of our t-test of comparing if there is a statistically significant difference between wildfire severity trends in countries with the lowest wildfire severity, Quintile 1, and countries with the highest wildfire severity, Quintile 5.

In Table 6, we report the t-test results of whether or not there is a statistically significant difference in wildfire severity trends between countries with the most severe worsening of wildfire severity conditions and those with the least deterioration. The test produced a t-value of approximately -31, indicating a highly significant difference between the two groups and that the mean trend in Quintile 1 indeed is lower than in Quintile 5. In that way, the results of the t-test decisively indicate a statistically significant difference in wildfire severity trends between the two groups. Countries in Quintile 1 are experiencing a trend towards less severe wildfire severity, in contrast to those in Quintile 5, who are seeing a trend towards worsening wildfire severity. This finding is critical for understanding the geographical disparities in the impact of climate change.

**Table 7.** Change in Profitability to Portfolios Sorted on Wildfire Severity Time Trend

| Portfolio | (t,t+1) | (t,t+2) | (t,t+3) |
|---|---|---|---|
| **Quintile 1** | 1.69% | 2.78% | 2.17% |
| **Quintiles 2-4** | 0.91% | 0.88% | 1.56% |
| **Quintile 5** | 1.52% | 2.37% | 2.08% |
| **1 - 5** | 0.17% | 0.42% | 0.09% |
| **T-statistic** | 0.09 | 0.16 | 0.03 |

The table displays the results of the change in forestry and P&P industry profitability for all Quintile portfolios as well as for the long/short 1-5 portfolio for one-, two-, and three-year holding horizons, respectively. We report the corresponding t-statistic for all holding horizons.

Table 7 displays the change in industry profitability for our five quintiles. Countries belonging to Quintile 1 have an average increase of 1.69%, 2.78%, and 2.17% when looking 1, 2, and 3 years ahead, respectively. For Quintile 2 to 4 the change in profitability is 0.91%, 0.88%, and 1.56%. For Quintile 5 the increase is 1.52%, 2.37%, and 2.08%. Lastly, the difference between the countries experiencing the less severe wildfire severity trend, Quintile 1, compared to those experiencing the most severe wildfire severity trend, Quintile 5, is 0.17%, 0.42%, and 0.09%, respectively. However, since the t-statistic is 0.09, 0.16, and 0.03 for the three periods, the difference in change in forestry and P&P industry profitability between Quintile 1 and Quintile 5 is not significantly different from 0 for any time period.

**Table 8.** Fama-MacBeth Regression on Change in Forestry and P&P Industry Profitability on Fire Severity Time Trend. **Panel A.** Ranking Based on Estimated Fire Severity Trend at the End of Each Year

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| **Const** | 1.055** (2.5449) | 1.0493 (1.2821) | -1.6622 (-1.0571) |
| **TrendQuintile5** | 0.7516 (0.5688) | -1.0875 (-1.3931) | -2.8227* (-2.0756) |
| **PB** | | -0.1498 (-0.0886) | -0.1224 (-0.0705) |
| **FPPRET12** | | -0.0293* (-2.0975) | -0.0552*** (-3.4146) |
| **DP** | | | 0.458** (2.6098) |
| **MRET12** | | | 0.1546** (3.154) |
| **INF12** | | | 0.2869 (1.0326) |
| **R Squared** | 0.0857 | 0.2598 | 0.4573 |
| **Number of Observations (n)** | 126 | 126 | 126 |
| **Number of Countries (N)** | 14 | 14 | 14 |

The table displays the change in forestry and P&P industry profitability on fire severity trend for the variables forestry and P&P industry profitability $CP$, 12-month future forestry and P&P industry $FPPRET12$, 12-month lagged market return $MRET12$, forestry and P&P price-to-book ratio $FPPPB$, dividend/price ratio $DP$, 12-month lagged inflation rate $INF12$, and the end-year wildfire severity trend value $Trend$. The number of observations (n) is 126 and number of countries (N) is 14. We report the R squared for each regression.
*** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1

In Table 8, Panel A, we report the results of our regression of change in forestry and P&P industry profitability based on rankings of trends in fire risk at the end of each year. *, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively, with our t-statistic for each variable reported in the parenthesis. As seen in the first regression in column one, the variable $TrendQuintile5$ is positive although not significant. While this could indicate belonging to $TrendQuintile5$ is positively correlated with our dependent variable, the change in profitability $CP$, this relationship is not statistically significant and therefore suggests that the independent variable in isolation does not have a discernible impact on the dependent variable. For our second regression in column 2, the variable $TrendQuintile5$ is negative but not significant, indicating that the variable does not serve as a strong predictor for changes in our dependent variable. Out control variable $FPPRET12$ is negative and significant, indicating that an increase in the lagged industry return has a negative impact on the future change in profitability. In our third regression with all control variables included, presented in column 3, $TrendQuintile5$ is negative and significant at the 10% level. This indicates that belonging to the $TrendQuintile5$ Quintile has a negative effect on future change in profitability. Our control variables $FPPRET12$ is negative and significant at the 1% level, while $DP$ and $MRET12$ are positive and significant at the 5% level. This suggests that the $TrendQuintile5$ variable and the lagged forestry and P&P industry profitability are inversely related to the dependent variable while the lagged market return and dividend-to-price ratio are positively related to the dependent variable, making the variables all relevant factors in this model.

**Table 9.** Fama-MacBeth Regression on Change in Forestry and P&P Industry Profitability on Fire Severity Time Trend. **Panel B.** Ranking Based on Estimated Fire Severity Trend at the End of 2012

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| **Const** | 1.186** (2.883) | 0.9268 (1.1683) | -0.1891 (-0.2278) |
| **TrendQuintile5_2012** | -0.1657 (-0.3811) | -0.0371 (-0.0429) | -1.1559 (-1.1701) |
| **PB** | | 0.4266 (0.2251) | 0.0612 (0.0351) |
| **FPPRET12** | | -0.029* (-2.0029) | -0.0469*** (-4.5832) |
| **DP** | | | 0.0721 (0.292) |
| **MRET12** | | | 0.1206*** (3.5778) |
| **INF12** | | | 0.1302 (0.5112) |
| **R Squared** | 0.0667 | 0.2485 | 0.4503 |
| **Number of Observations (n)** | 126 | 126 | 126 |
| **Number of Countries (N)** | 14 | 14 | 14 |

The table displays the change in forestry and P&P industry profitability on fire severity trend at the end of 2012 for the variables forestry and P&P industry profitability $CP$, 12-month future forestry and P&P industry $FPPRET12$, 12-month lagged market return $MRET12$, forestry and P&P price-to-book ratio $FPPPB$, dividend/price ratio $DP$, 12-month lagged inflation rate $INF12$, and the end-year wildfire severity trend value $Trend$. The number of observations (n) is 126 and number of countries (N) is 14. We report the R squared for each regression.
*** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1

In Table 9, Panel B, we report the results for our regressions on change in forestry and P&P industry profitability based on rankings of trends in wildfire severity at the end of 2012. In our first regression, column 1, $TrendQuintile5\_2012$ is negative but not significant. As such, controlling for ranking based on estimated fire risk at the end of 2012 does not indicate that $TrendQuintile5\_2012$ has an impact on the dependent variable. For our second regression in column 2, $TrendQuintile5\_2012$ is again negative but not significant. Similarly to Panel A our lagged industry return is negative and significant while price-to-book is not significant. In our third regression in column 3, $TrendQuintile5\_2012$ remains negative and insignificant when taking into account all control variables. In much the same way as Panel A, however, our control variable $FPPRET12$ is negative and significant at the 1% level while $MRET12$ is still positive but now significant at the 1% level. $DP$ is positive but not significant. This points towards the lagged forestry and P&P industry profitability being inversely related to the dependent variable while an increase of the 12-month lagged market return also increases our dependent variable based on our ranking of wildfire severity trend on estimated wildfire severity at the end of 2012, similar to Panel A.

**Table 10.** Returns to Portfolios Sorted on Fire Severity Time Trend. **Panel A.** One-Year Holding Horizon

| Quintile | Excess Return | CAPM | Fama-French 3-Factor |
|---|---|---|---|
| **Quintile 1** | 1.42 | 1.38 | 1.36 |
| **Quintile 2-4** | 1.36 | 1.34 | 1.31 |
| **Quintile 5** | 1.96 | 1.94 | 1.90 |
| **1-5** | -0.54 | -0.56 | -0.54 |
| **t-stat (1-5)** | -3.00 | -3.10 | -2.98 |

The table displays the returns to portfolios for Quintiles 1 to 5 as well as the long/short 1-5 portfolio, sorted on fire severity time trend for a one-year holding horizon. We report the corresponding t-statistic for the holding horizons.

**Table 11.** Returns to Portfolios Sorted on Fire Severity Time Trend. **Panel B.** Two-Year Holding Horizon

| Quintile | Excess Return | CAPM | Fama-French 3-Factor |
|---|---|---|---|
| **Quintile 1** | 1.57 | 1.56 | 1.56 |
| **Quintile 2-4** | 1.39 | 1.38 | 1.37 |
| **Quintile 5** | 2.14 | 2.14 | 2.15 |
| **1-5** | -0.56 | -0.58 | -0.59 |
| **t-stat (1-5)** | -4.76 | -4.88 | -4.90 |

The table displays the returns to portfolios for Quintiles 1 to 5 as well as the long/short 1-5 portfolio, sorted on fire severity time trend for a two-year holding horizon. We report the corresponding t-statistic for the holding horizons.

**Table 12.** Returns to Portfolios Sorted on Fire Severity Time Trend. **Panel C.** Three-Year Holding Horizon

| Quintile | Excess Return | CAPM | Fama-French 3-Factor |
|---|---|---|---|
| **Quintile 1** | 1.61 | 1.60 | 1.60 |
| **Quintile 2-4** | 1.30 | 1.30 | 1.30 |
| **Quintile 5** | 1.87 | 1.88 | 1.88 |
| **1-5** | -0.27 | -0.28 | -0.28 |
| **t-stat (1-5)** | -3.18 | -3.30 | -3.29 |

The table displays the returns to portfolios for Quintiles 1 to 5 as well as the long/short 1-5 portfolio, sorted on fire severity time trend for a three-year holding horizon. We report the corresponding t-statistic for the holding horizons.

In Table 10, Table 11, and Table 12, we can see the Excess Return, CAPM alpha, and the Fama-French three-factor alpha for portfolios belonging to Quintile 5, Quintile 2 to 4, Quintile 1, and Quintile 1-5, with the corresponding t-statistic. Panel A represents a one-year holding, Panel B a two-year holding and Panel C a three-year holding period. Noteworthy is that all quintiles have a positive alpha for all our asset pricing models, meaning that our industries have overperformed overall. Looking at the one-year holdings, the Fama-French three-factor model, which is our most stringent asset pricing model, has a negative return of -0.60 for our long/short (1-5) portfolio with t-statistic of -4.13, indicating a high statistical significance. In Panel B, with a two-year holding period, the long/short portfolio has a negative return of -0.58 with a t-statistic of -4.25, again indicating a high statistical significance. Similarly for the three-year holdings the long/short portfolio has a return of

-0.27 with a t-statistic of -3.21, again with a high statistical significance. These results indicate that creating a self-financed portfolio by investing in a portfolio consisting of all the firms in Quintile 5 while going short all the companies in Quintile 1 would have a positive return for all holding periods.

**Table 13.** Fama-MacBeth Regression on Future 12-Month Non-Overlapping Forestry and P&P Return on Fire Severity Time Trend. **Panel A.** Ranking Based on Estimated Fire Severity Trend at the End of Each Year

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| **Const** | 0.1772*** (6.7618) | 0.1458*** (3.5187) | -0.0082 (-0.1482) |
| **TrendQuintile5** | 0.2812** (2.7245) | 0.2693 (1.7505) | 0.081 (1.4315) |
| **PB** | | 0.0612 (0.0351) | 0.0612 (0.0351) |
| **FPPRET12** | | 0.0016 (0.6716) | 0.0023 (1.5859) |
| **DP** | | | 0.0453** (2.895) |
| **MRET12** | | | 0.0018 (0.5524) |
| **INF12** | | | 0.0157 (1.2364) |
| **R Squared** | 0.1111 | 0.3708 | 0.6472 |
| **Number of Observations (n)** | 126 | 126 | 126 |
| **Number of Countries (N)** | 14 | 14 | 14 |

The table displays the future 12-month non-overlapping forestry and P&P industry profitability on fire severity time trend at the end of each year for the variables $TrendQuintile5$, which is a dummy variable taking the value 1 for the countries with the worst wildfire severity trend and 0 otherwise, the trend forestry and P&P industry profitability $CP$, the 12-month future forestry and P&P industry $FPPRET12$, the 12-month lagged market return $MRET12$, the forestry and P&P price-to-book ratio $FPPPB$, the dividend/price ratio $DP$, and the 12-month lagged inflation rate $INF12$. The number of observations (n) is 126 and number of countries (N) is 14. We report the R squared for each regression.
*** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1

Table 13, Panel A, presents the results of our Fama-Macbeth regressions of the future 12-month non-overlapping forestry and P&P returns on wildfire severity time trend and the end of each year. In our first regression, column 1, we observe a positive and significant result of our variable $TrendQuintile5$ at the 5% significance level, indicating a strong and positive correlation between belonging to $TrendQuintile5$ and future 12-month returns. For our second regression in column 2, where we have added the two control variables $PB$ and $FPPRET12$, our independent variable $TrendQuintile5$ is still positive, nevertheless with no significance. This suggests that adding these two control variables moderates the effect of $TrendQuintile5$ which no longer remains a significant predictor for the future returns. As can be seen in our third regression in column 3, where all our control variables are added, the $TrendQuintile5$ variable is positive but still insignificant. However, our control variable $DP$ is positive and significant at the 5% significance level. This progression, where our independent variable as a result of including additional control variables moves from being notably positive and strongly significant in the first regression to being negligible positive and insignificant indicates that the combined effect of the included control variables mask the effect of our independent variable, suggesting that the initial impact of $TrendQuintile5$ in our model is attributable to factors represented in the control variables.

**Table 14.** Fama-MacBeth Regression on Future 12-Month Non-Overlapping Forestry and P&P Return on Fire Severity Time Trend. **Panel B.** Ranking Based on Estimated Fire Severity Trend at the End of 2012

| Variable | (1) | (2) | (3) |
|---|---|---|---|
| **Const** | 0.2065*** (4.2227) | 0.1505*** (4.6958) | 0.0208 (0.4119) |
| **TrendQuintile5__2012** | 0.0759 (1.0027) | 0.0589 (1.0802) | 0.0824** (2.9037) |
| **PB** | | 0.0612 (0.0351) | 0.0612 (0.0351) |
| **FPPRET12** | | 0.0019 (0.7274) | 0.0024 (1.7269) |
| **DP** | | | 0.036** (2.718) |
| **MRET12** | | | 0.0004 (0.1136) |
| **INF12** | | | 0.0176 (1.3689) |
| **R Squared** | 0.0738 | 0.3244 | 0.633 |
| **Number of Observations (n)** | 126 | 126 | 126 |
| **Number of Countries (N)** | 14 | 14 | 14 |

The table displays the future 12-month non-overlapping forestry and P&P industry profitability on fire severity time trend at the end 2012 for the variables $TrendQuintile5$, which is a dummy variable taking the value 1 for the countries with the worst wildfire severity trend and 0 otherwise, the trend forestry and P&P industry profitability $CP$, the 12-month future forestry and P&P industry $FPPRET12$, the 12-month lagged market return $MRET12$, the forestry and P&P price-to-book ratio $FPPPB$, the dividend/price ratio $DP$, and the 12-month lagged inflation rate $INF12$. The number of observations (n) is 126 and number of countries (N) is 14. We report the R squared for each regression.
*** P-value < 0.01, ** P-value < 0.05, * P-value < 0.1

In Table 14, Panel B, we have a positive and insignificant result of our independent variable $TrendQuintile5\_2012$ in our first regression. As can be seen in our second regression in column 2, $TrendQuintile5\_2012$ is still positive and insignificant when including the control variable $PB$ and $FPPRET12$. However, when including all control variables in our third regression in column 3, $TrendQuintile5\_2012$ is still positive but now significant at the 5% significance level. This suggests that belonging to the $TrendQuintile5\_2012$ countries, where the dummy variable takes the value 1, has a positive effect on future profitability. Our control variable $DP$ is significant at the 5% significance level. This illustrates the substantial influence of the included control variables and suggests that the effect of $TrendQuintile5\_2012$ is conditional upon the presence of other variables that might be overshadowed in the model.

# 7. Discussion

## 7.1 Analysis

Our results from Regression 1 shows a significant heterogeneity in wildfire severity trends between different countries, consistent with climate studies showing that there are geographical winners and losers regarding the effects of climate change (Adachi and Li, 2023; Wang and Lewis, 2023). Having sorted the countries into quintiles, our results show that there is a significant difference between the trend of the Quintile 1 and Quintile 5 countries, meaning that there is a meaningful differentiation between the groups. To investigate our first hypothesis, we then examined if any difference in forestry and P&P profitability growth for these different quintiles could be discerned. In Table 7, we noticed a marginally better future profitability for the countries with the best trend compared to those with the worst trend for one-, two-, and three-year holding horizons, respectively. However, it is important to note that the t-statistic for all of these comparisons was low, indicating that we cannot discern any difference between the quintiles. This stands in contrast to the results of Hong, Wekai Li and Xu (2018) that showed a significant outperformance for their quintile with the best (decreasing) drought trend compared to their quintile with the worst (increasing) drought trend. However, there is a large difference in total number of countries, number of countries per quintile, the total number of firms per country, and the length of the studied time period for the drought as well as the firm data. All of these differences affect the robustness of the results as well as the likelihood of showing significant results.

In addition to the portfolio sorts, we also ran regressions where we added control variables to check the robustness of our portfolio sort results. Having added all of our control variables, we found a significant effect of our primary variable of interest, $TrendQuintile5$, meaning that belonging to countries sorted in the worst quintile predicted a negative future profitability in comparison to the countries sorted on other quintiles, which was in line with our first hypothesis. Nevertheless, this predictive variable should not affect the future returns of stocks in this quintile according to the Efficient Market Hypothesis, as all publicly available information should be reflected in the price of an asset. This means that our publicly available wildfire data and the trends we find should already be priced in for all publicly traded stock companies. To assess whether our second hypothesis was supported, we wanted to assess if the market is efficiently accounting for these trends in wildfire severity between countries. Looking at Table 10, 11, and 12, we surprisingly see that for all holding periods Quintile 5 outperforms Quintile 1 with a high statistical significance. The results of Panel A, Panel B and Panel C stand in contrast to the Efficient Market Hypothesis as this would mean that publicly available information has a predictive power on future returns. A self-financed portfolio going long Quintile 5 and short Quintile 1 would achieve a positive return which, in theory, would imply an arbitrage opportunity. This result is partly in line with Hong, Wekai Li and Xu (2018) that also found that the returns violated the Efficient Market Hypothesis. However, our results suggest the opposite of theirs, namely that the market overreacts to climate risks as proxied by our wildfire severity trends. Our placebo analysis, which used non-forestry and P&P industries, did not display any significant differences between the quintiles, which demonstrates that we are identifying climate change risks related to wildfire severity and that our main results are not driven by unobserved differences in country-specific characteristics. Another interesting finding is that all quintiles achieve a positive alpha, both according to the CAPM and Fama-French three-factor models, regardless of the holding horizon. As such, this provides evidence, and can act as a rationale, for investing in these particular industries. Although this is not our primary research objective it is a noteworthy finding.

We further investigate the predictive power of our wildfire severity trends on future portfolio returns by our regressions in Table 13. Our first regression without control variables indicates an overperformance of Quintile 5 compared to all other quintiles. Again, this indicates that the market is not efficient. In line with our earlier results, Quintile 5 can be stated to be underpriced as the returns for this quintile is better than the other quintiles. A possible explanation for this overperformance could be overly risk-avert investors selling and avoiding these stocks, which is in accordance with theories from behavioral finance. In our second and third regressions with control variables added, the $TrendQuintile5$ variable is still positive. However, it is no longer significant which means that we cannot state that the market is inefficient and suggests that our earlier results could be explained by omitted variable bias. This is in contrast to the findings of Hong, Wekai Li and Xu (2018) that indicated that the market is indeed inefficient and underestimates the risk of climate change.

Possible explanations to this difference in results can be the aforementioned shorter time period as well as the fewer number of firms and countries of our study compared to theirs. Additionally, the homogeneity in countries and consequently markets which we study can be assumed to be more efficient because of better institutions and less uncertainty compared to the more diverse countries in their study. We believe that this homogeneity in country characteristics may strengthen our results compared to Hong, Wekai Li and Xu (2018) which will have more confounding factors through uncontrolled variation in institutional stability. Our regression results of Table 8, Panel A, and Table 9, Panel B, are in general similar regarding sign, size of the effect, and significance level with a few exceptions, suggesting that our wildfire severity trend measures are stable over time and that we are measuring long-term trends rather than temporary fluctuations in weather conditions. Similarly for Table 13, Panel A, and Table 14, Panel B, we generally see the same results which strengthen these findings. In our placebo tests where we randomized which countries belong to the $TrendQuintile5$, we can observe that our coefficients fall in the middle of the random distribution, meaning that it could be due to us observing noise. The aforementioned differences in time periods, especially for the firm data and stock returns, could be one of the explanations why these results are not robust.

## 7.2 Limitations

Our wildfire severity data is built on a time period of 20 years, compared to Hong, Wekai Li and Xu (2018) which had a time period of more than 100 years. To examine the effects of climate change, we need a longer time period which means that our dataset is a limitation. Our trends up until the end of 2012, which we use to control if our trend results seem to be robust over time and not temporary fluctuation, have an even shorter time period, thereby being further limited than our main trends. Additionally, the industries we have chosen and believe are most affected by an increase in wildfires and wildfire severity have somewhat few firms per country. More specifically, we have filtered out countries with less than two firms, leaving us with 14 countries compared to 31 of Hong, Wekai Li and Xu's (2018) study. However, a majority of our countries still have less than 10 firms, the limit that Hong, Wekai Li and Xu (2018) used, meaning that firm-specific events that have no relation to wildfires can have large effects on countries' change in profitability and future stock returns. Furthermore, with the decrease in total number of countries compared to Hong, Wekai Li and Xu (2018), each country has a larger effect on the quintile performance, leading to less robust results which is an additional limitation. Another limitation is potential omitted variable bias as there are other variables influencing both the profitability and stock returns that we are not able to include in our regressions. We are neither controlling for country-specific effects, although that is in part negated by looking at quintile data instead of country data. However, this does not fully substitute for controlling for country-specific effects. The underlying country-specific factors could still disproportionately affect the data in each quintile, especially as our number of countries per quintile is low.

Even though the Daily Severity Rating has a component that reflects the expected efforts required for fire suppressions, an additional limitation could be that the trends that are based on this index does not necessarily lead to impactful wildfires. More specifically, it is a proxy for climate change and wildfire impact and may therefore not exactly align with those. Moreover, a limitation of our study could be a lack of consistency of the wildfire trend over the analyzed period, where we can see a difference in wildfire trend in 2012 as well as over the whole sample period. However, while the decision to choose 2012 as a comparative year is due to our stock return data beginning in the following year, 2013, this only display that there is a difference between the trend in wildfire severity in 2012 compared to the whole period, and does not necessarily show that there is an inconsistency surrounding the other years. A further limitation is potential endogeneity as the forestry and P&P industries can both affect as well as be affected by wildfires, creating a bidirectional relationship. For example, silviculture practices may influence wildfire frequency and severity, while wildfires can significantly impact the productivity and sustainability of these industries. Lastly, our stock return sample period includes the Covid-19 period which had a large effect on the stock market. As our total sample period is only 10 years, this might have an impact on our results which is not related to our wildfire severity trends.

# 8. Concluding Remarks

## 8.1 Conclusion

Wildfires are becoming increasingly potent due to factors such as climate change and agricultural practices. The negative consequences are not seldom catastrophic for societies and local populations, resulting in human casualties. In addition to the tragic loss of lives, wildfires have a substantial negative impact on assets running from real estate, forestry and infrastructure. Hence, this constitutes a new and unexplored economic area of research that offers many insightful learnings. In this study, we investigate if wildfire severity has a material impact on companies within the forestry and P&P industries and whether or not the stock market correctly prices these risks in accordance with the Efficient Market Hypothesis. As such, we construct wildfire severity trends on a set of European countries, study the material impact of these trends on firm-specific net income through a set of regressions on different portfolio sorts, and measure the stock market's response to this information. More specifically, we run cross-country regressions for our dependent variable being the one-year future change in profitability. Thereafter, we run a set of identical regressions on the 12-month future forestry and P&P industry returns as our dependent variable in order to examine if there is a correlation between our independent variable and future stock returns. Additionally, we conduct a placebo test to assess the robustness and validity of our results. Since few studies have been conducted within our specific research area, we base our study on research topics ranging from climate disaster events and the effects on asset prices, wildfires and the effects on asset prices, as well as climate disaster events and market response.

We find support for a statistical difference in wildfire trends across the analyzed countries, where the countries experiencing the least severe trend in terms of wildfire severity, Quintile 1, is strongly different from the companies belonging to the most severe trend in wildfire severity, Quintile 5. This is an important initial conclusion as it conveys a meaningful differentiation between companies belonging to different countries experiencing different wildfire severity, where they have statistically different means, and provides cues for the countries' different geographical settings. While we do not find any statistical difference of the change in forestry and P&P industry profitability when in isolation comparing companies situated in countries experiencing the least severe wildfire severity trend, Quintile 1, compared to those situated in countries experiencing the most severe wildfire severity trend, Quintile 5, we do find statistical evidence that belonging to Quintile 5 has a significantly negative impact on forestry and P&P industry profitability compared to belonging to any other quintile when doing a regression together with a set of control variables. As a control to see if our trends are stable over time and not capturing temporary climate fluctuations, we also conducted the same profitability regressions although instead based on the trend up until 2012. Our results of these regressions are generally the same as for our rolling trends, with the same sign for almost all variables and mostly the same significance levels. However, our primary variable of interest, $TrendQuintile5\_2012$, is no longer significant. This does not invalidate our conclusions that the change in profitability is negatively correlated with wildfire severity trends but instead indicates that our trends may be capturing temporary climate changes rather than long-term trends. We control for multicollinearity and conclude that this is not present for our independent variables. However, our placebo tests indicate that our regression results might be based on noise rather than actual effect. When regressing the returns for the quintile portfolios on different holding horizons, we find evidence that holding a long/short portfolio of Quintile 5 - 1 for one, two, or three years has a statistically significant positive alpha when using both the CAPM as well as the Fama-French three-factor model, suggesting that the stock market is not efficiently pricing these wildfire severity trends. In addition, we observed a positive alpha across all quintiles, suggesting that the forestry and P&P industries outperform the stock market. When taking our regression with control variables into account, however, we conclude that this outperformance does not derive from belonging to Quintile 5 but instead from other factors. As such, we cannot reject the null hypothesis that belonging to Quintile 5 has no effect on future stock returns, which would indicate that the market indeed is efficiently pricing climate change risk as proxied by wildfire severity.

To conclude, our study finds that trends in wildfires have a material impact on forestry and P&P industries in terms of future profitability. Furthermore, our results indicate that the market is indeed efficiently pricing the risks associated with wildfires in terms of companies' profitability and thus supports the Efficient Market Hypothesis. As such, we hope that our study and findings can support future decision makers in making efforts to mitigate climate change, as well as serve as a foundation for forestry owners and investors when making investments, either directly or through the stock market, in this form of asset.

## 8.2 Future Research

The study of market efficiency in the context of climate disaster events and wildfires is an interesting field of research. With increasing occurrence of wildfires and a surge in public concern pertaining to climate change, it is of large interest to understand the economic impact of these climate disaster events and how market actors are responding to wildfire severity in the light of finance theory. Consequently, we believe that future research could increase the geographical scope of our study by including a more diverse set of countries and companies, especially in countries that have undertaken societal actions to decrease wildfire severity in order to discern the potential effects on climate change. This could furthermore be extended beyond the forestry and P&P industries in order to examine the broader economic impact of wildfires and wildfire severity. As mentioned in our earlier discussion, addressing the limitation of potential issues with the trend in wildfire severity over time could moreover be an area for future research, where one could study how strong and consistent the trend in wildfire severity is over time as this can have implications for the stock market's ability to correctly anticipate wildfire severity trends and their impacts on firm fundamentals. As such, this could have an effect on stock market responses to these wildfire severities and be important factors to take into account when conducting research aimed at establishing causal inference between these variables, as well as whether or not the stock markets are efficient. While our study examines a set of countries in an aggregated form, additional research efforts could be directed towards in-depth analysis on specific countries and the diverse effects of wildfires on countries and asset prices. Lastly, since our study does not directly measure behavioral aspects of investors following wildfires or wildfire severity trends, it would be interesting to conduct an event study aimed at investigating the effects of information regarding wildfires on investor sentiment and trading behavior. As such, intricacies or novel findings surrounding market efficiency in a research area growing ever-more important could potentially be found.

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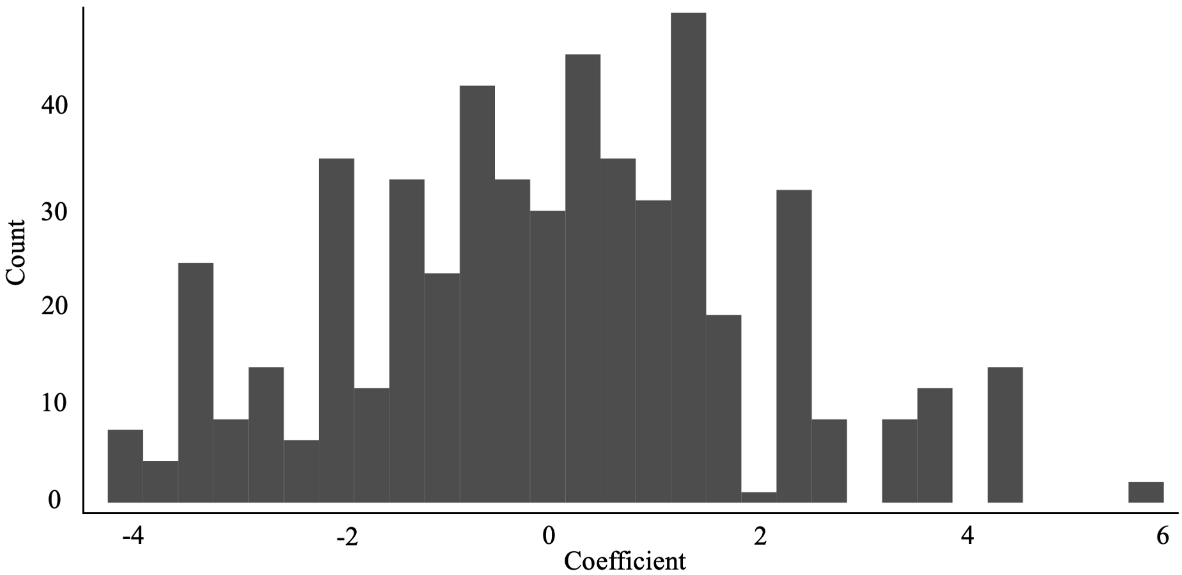
# Appendix

**Table 15.** Average Number of Fires Per Year

| Country | Average Number of Fires Per Year |
|---|---|
| Italy | 276 |
| Portugal | 207 |
| Spain | 191 |
| Turkey | 121 |
| France | 72 |
| Greece | 57 |
| United Kingdom | 33 |
| Sweden | 7 |
| Germany | 5 |
| Norway | 5 |
| Finland | 1 |
| Denmark | 1 |
| Poland | 1 |
| Switzerland | 0 |

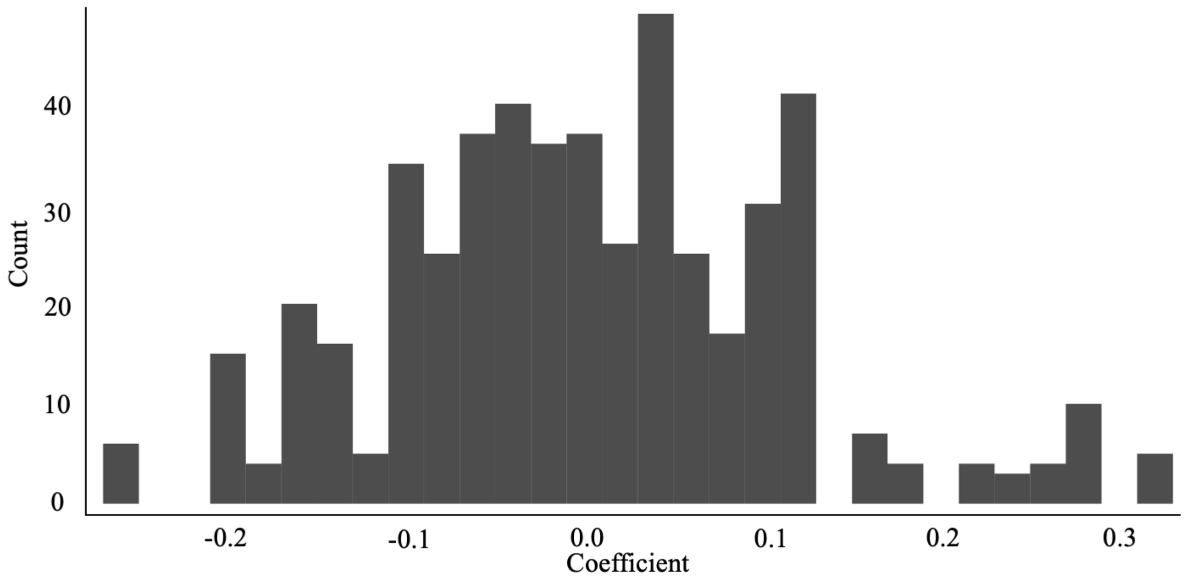
The table reports the average number of wildfires per year for the countries in our dataset, based on data from the European Forest Fire Information System (EFFIS).

**Figure 4.** Distribution of Coefficients When Randomizing Quintile5 in the Fama-MacBeth Regression on Change in Forestry and P&P Industry Profitability on Fire Severity Time Trend, Ranking Based on Estimated Fire Severity Trend at the End of Each Year




The figure reports the distribution of coefficients when randomizing Quintile5 500 times in the Fama-MacBeth regression on change in forestry and P&P industry profitability on fire severity time trend, ranking based on estimated fire severity trend at the end of each year (robustness check of Table 8, Panel A).

**Figure 5.** Distribution of Coefficients When Randomizing Quintile5 500 times in the Fama-MacBeth Regression on Future 12-Month Non-Overlapping Forestry and P&P Return on Fire Severity Time Trend, Ranking Based on Estimated Fire Severity Trend at the End of Each Year




The figure reports the distribution of coefficients when randomizing Quintile5 500 times in the Fama-MacBeth regression on future 12-month non-overlapping forestry and P&P return on fire severity time trend, ranking based on estimated fire severity trend at the end of each year (robustness check of Table 14, Panel A).

**Table 16.** Returns to Utilities Portfolios Sorted on Fire Severity Time Trend With a One-Year Holding Horizon

| Quintile | Excess Return | CAPM | Fama-French 3-Factor |
|---|---|---|---|
| **Quintile 1** | 0.65 | 0.63 | 0.62 |
| **Quintile 2-4** | 1.22 | 1.20 | 1.20 |
| **Quintile 5** | 0.94 | 0.94 | 1.00 |
| **1-5** | -0.29 | -0.31 | -0.37 |
| **t-stat (1-5)** | -1.03 | -1.09 | -1.38 |

The table displays the returns to portfolios for Quintiles 1 to 5 as well as the long/short 1-5 portfolio for the utilities industry, sorted on fire severity time trend for a one-year holding horizon. We report the corresponding t-statistic for the holding horizon.

**Table 17.** Returns to Healthcare Portfolios Sorted on Fire Severity Time Trend With a One-Year Holding Horizon

| Quintile | Excess Return | CAPM | Fama-French 3-Factor |
|---|---|---|---|
| **Quintile 1** | 1.55 | 1.51 | 1.50 |
| **Quintile 2-4** | 1.35 | 1.32 | 1.28 |
| **Quintile 5** | 1.47 | 1.45 | 1.44 |
| **1-5** | 0.08 | 0.06 | 0.06 |
| **t-stat (1-5)** | 0.34 | 0.26 | 0.25 |

The table displays the returns to portfolios for Quintiles 1 to 5 as well as the long/short 1-5 portfolio for the healthcare industry, sorted on fire severity time trend for a one-year holding horizon. We report the corresponding t-statistic for the holding horizon.