UiT Norges arktiske universitet

School of Business and Economics

Do investors care about disclosed climate change risk?

A study of how climate change risk disclosures affect the cross-section of US stock returns.

Morten Parschat and Petter Schive

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Abstract

In this paper we investigate whether firms' climate change risk disclosures affect the cross-section of US stock returns. We use a dataset constructed by an Artificial Intelligence (AI) algorithm, fine-tuned by Kölbel et al. (2021b), to classify climate change risk disclosures into Physical and Transitional risks. We find that after the Paris Agreement the disclosure of physical risk is associated with a significant positive risk premium. This premium is consistent and not explained by industry variation or other well-known risk factors. We find no consistent premium related to the disclosures of transitional risk. Our results suggests that investors attention towards the disclosures of physical climate change risk increased after the Paris Agreement. Overall, we find that investors view the disclosures of physical climate change risk as informative and risk revealing.

Keywords: climate change, climate risk disclosure, Stock returns, 10-K filings, physical risks, transition risks

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1 Introduction

In relation to the Paris Agreement, the IPCC (2018) confirmed that a 2 degree Celsius increase in global temperature is significantly more damaging than a 1.5 degree increase. More recently, at COP 26 in Glasgow 2021, the overall sentiment was that the projections of today's emissions would not be in line with the overarching goal of a less than 2-degree global warming compared to pre-industrial levels. This development thus makes it clear that extensive and rapid CO2 emissions cuts must be implemented in all countries and in all sectors if the world is to stay on track to reach the 1.5-degree target. Even if the global temperature increase stops at 1.5-degrees, the IPCC (2018) states that physical climate change risks are greater at 1.5-degrees than at present, but notably lower than at 2-degrees. This poses huge challenges for the financial markets because it's unclear how and when individual firms will be affected by physical or transition shocks. Physical risk is the uncertainty regarding how extreme weather and other abnormal events, affect the firms and industries. Transition risk is the uncertainty of political and or technological changes that will be imposed during the adjustment to a lower-carbon economy.

Schoenmaker (2017) proposes two good reasons a reliable measurement on firm-level climate change risk is of importance; 1) Climate change risk can lead to large losses for firms, financial institutions and asset owners, 2) The main task of the financial system is to allocate funding to its most productive use, for which the assessment requires reliable measurements of risks. This means that if financial markets are pricing climate change risk effectively they will play an important role in allocating investments to sustainable companies and projects and thus accelerate the transition to a low-carbon economy (Schoenmaker, 2017). Alternatively, institutional long-term investors, such as the Norwegian Pension Fund will have a better understanding of their total climate change risk, and can take action to reduce it or play an active role in changing firms behavior. Based on this, a reliable climate risk exposure measurement may help mitigate these risks and contribute to the green transition.

This development has motivated several recent studies in the finance literature to investigate how climate change risk affects the financial markets. Bolton and Kacperczyk (2021) for example investigate how carbon emission affect stock returns.

Avramov et al. (2021) investigates the provider uncertainty of Environmental, Social and Governance scores (ESG). Berkman et al. (2021), Sautner et al. (2021), and Kölbel et al. (2021b) use textual analysis to investigate how earnings calls and disclosures in annual filings affect stock returns. However, this field of research is still in its early stage and currently there exists no consensus among academics or practitioners about how to reliably quantify firm-level climate change risk (Sautner et al., 2021). For this reason, we turn to an innovative method to assess whether regulatory disclosure of climate change risk affects the cross-section of US stock returns.

The starting point for our thesis is the paper by Kölbel et al. (2021b), who used an AI-based algorithm to quantify climate change risk disclosures in Item 1A of 10-k filings of US firms. The algorithm was fine-tuned by them to differentiate between physical and transitional risk and they note that the method is superior to previous methods of textual analysis. Further, they argue that climate change sentences in Item 1A, are a disclosure of climate change risk, because firms are required to disclose risks in this section of the filling.

Further, if investors care about the disclosure of climate change risk, the disclosure itself measures firms' climate change risk exposure. To assess whether the disclosure of climate change risk is of interest to investors, we form our hypothesis following Kravet and Muslu (2012) who suggests three arguments; the null argument, the divergence argument, and a convergence argument.

- H0: The null argument predicts that investors find the risk disclosure uninformative, meaning that investors do not care about the disclosure of climate change risk. If this is true, we would not be able to detect impact from the risk factor on the cross-section of stock returns.

- H1A: The divergence argument states that the risk disclosure reveals unknown risk factors and contribute to an increase in investors' risk perception. We should in this case be able to detect an impact on the cross-section of stock returns with a positive risk premium related to the disclosure of climate change risk.

- H1B: The convergence argument states that risk disclosure decreases investors' risk perception by confirming already known risk factors. Hence, the risk premium observed should be negative related to the disclosure of climate change risk.

Additionally, we test whether specific industries (oil, gas, utilities, transportation etc.) or events (Paris Agreement/Trump election) are the main drivers for our results or pivotal points for investor attention. For our main analysis, we look at monthly returns for the time period from 2010 to 2020 and run pooled OLS regressions with time and industry fixed effects . For data on the disclosure of climate risk, we turn to the publicly available dataset from Kölbel et al. (2021a) and match this with financial data from FactSet. Further, we control for firm characteristics known to impact returns before extracting the monthly cross-sectional return premiums. Then we test whether the observed premiums are related to the traditional risk factors.

Broadly, our findings indicate that not all climate change disclosure is of importance to investors. We find evidence that suggests there to be a positive return premium for the disclosure of physical climate change risk, especially for the time-period after the Paris Agreement. The risk premium associated with physical climate change risk disclosure is of statistical and economical significance. However, we find no significant association between transitional risk and stock returns. This further suggests that physical risk and transitional risk should be analyzed individually. The return premium for physical climate change risk reflects a lower investor demand for firms that disclose greater amounts of physical climate change risk.

We structure the thesis as follows: We start by presenting central theories in the field of finance and a literature review on climate change finance. Next, we use empirical analysis to investigate what firm characteristics can explain the disclosure of climate change risk. We then assess whether this risk has significant explanatory power on the cross-sectional returns. We extract the cross-sectional returns, as it is the risk premium for a long-short zero net investment climate risk weighted portfolio. As a robustness test, we test whether specific industries asymmetrically affect the results. Additionally, we adjust for industry specific risk regarding climate change Materiality based on the SASB Materiality Map®. Finally we test if the Paris Agreement has affected the market.

2 Theory and literature review

In this section we present original work that have shaped how we think about finance today. We first start by introducing the modern portfolio theory. Then we explain how this theory made the foundation of The Capital Asset Pricing Model (CAPM). Finally, we present factor models that originated from the shortcomings of CAPM.

2.1 Modern Portfolio Theory

For financial theory we start with Markowitz (1952) who introduced the modern portfolio theory. Markowitz diversification involves combining assets with less-than-perfect positive correlations in order to reduce risk in the portfolio without sacrificing the portfolios return. The theory implies that neither risk nor return should be evaluated separately, but from a portfolio perspective, by looking at total risk and the expected return. Based on modern portfolio theory, the return on a portfolio of multiple assets is given by:

$$E(r_p) = \sum_{i=1}^{n} w_i E(r_i) \tag{1}$$

Where:

$E(r_p)$ = Expected return on portfolio p.

w_i = Weight of portfolio p in asset i

$E(r_i)$ = Expected return on asset i

The portfolio risk is given by the following equation:

$$\sigma_p^2 = \sum_{i=1}^{n} \sum_{j=1}^{n} \binom{n}{k} w_i w_j \sigma_{i,j} \tag{2}$$

Where:

σ_p^2 = Variance of portfolio p.

w_i = Weight in asset i

w_j = Weight in asset j

$\sigma_{i,j}$ = Covariance between asset i and j

Covariance is given by:

$$\sigma_{i,j} = \rho_{i,j}\sigma_i\sigma_j \tag{3}$$

Where:

$\rho_{i,j}$ = Covariance between asset i and j

σ_i , σ_j = Standard deviation on asset j and asset i

Markowitz (1952) showed that portfolio risk is given by the portfolio variance, and that this variance is given by the correlation between the different assets in the portfolio. In general, the lower the correlation between the assets in a portfolio, the less risky the portfolio will be (Kim & Francis, 2013). The Portfolio Theory of Markowitz (1952) is based on some assumptions:

- Investors are rational and behave in a manner as to maximize their utility with a given level of return.
- Investors have free access to fair and correct information on the returns and risk.
- The markets are efficient and absorb the information quickly and perfectly.
- Investors want to minimize the risk and maximize return.
- Investors base decisions on expected return and standard deviation of these returns.
- Investors choose higher returns to lower returns for a given level of risk.

These risk-return opportunities that are available to the investors are summarized by minimum-variance frontier of risky assets (Bodie & Kane, 2020). Based on Markowitz assumptions for investor behavior, no rational investor will choose a portfolio with higher risk if it is possible to achieve the same return with lower risk (Bodie & Kane, 2020). The part of the frontier which is below the global minimum-variance portfolio is inefficient because an investor can obtain higher return with the same level of risk. A rational investor will therefore only hold a combination laying on the efficient frontier.

The second part of the portfolio optimization, based on modern portfolio theory, involves a risk-free asset. Further, since we assume investors the same opportunities, they will end up with the same capital allocation (Bodie & Kane, 2020). Further, since we assume that investors have the same opportunities, they will end up with the same combination of the risk free asset and the optimal portfolio (Bodie & Kane, 2020). This combination represents the highest risk reward that investors can have. The amount of assets invested into the risk-free rate is therefore dependent on the risk aversion of the individual investors. The risk reward trade-off is measured by the excess return of a portfolio divided by the volatility of the portfolio. This reward-to-volatility measure was first used extensively by William Sharpe and hence is commonly known as the Sharpe Ratio (Bodie & Kane, 2020). The Sharpe ratio is given by:

$$SharpeRatio = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

Where:

R_{p} = the return of the portfolio

R_{f} = the risk free rate

σ_{p} = the volatility of the portfolio

2.2 Capital Asset Pricing Model

The Capital Asset Pricing Model (CAPM) is one of the centerpieces of modern financial economics. This model is based on modern portfolio management and provides a methodology to quantify risk and translate that risk into estimates of expected return on equity (Bodie & Kane, 2020). It was published in articles by Sharpe (1964), Lintner (1965) and Mossin (1966) who wanted to find a theoretical explanation of why a risk premium exists (Bodie & Kane, 2020). CAPM is based on Modern Portfolio Theory and assumes that investors are risk averse and choose efficient portfolios. The formal development of CAPM involves other, more specialized limiting assumptions. These include frictionless markets, without transaction costs, taxes and restrictions on borrowing and short selling. Sharpe (1964) and Lintner (1965) add the assumption about homogenous expectations among investors about risk and expected return and that they can borrow and lend at the risk-free rate (Bodie & Kane, 2020). CAPM is given by:

$$E(r_p) = r_f + \beta_p[E(r_m) - r_f] \tag{5}$$

Where:
$E(r_p)$= Expected return on portfolio p.
r_f = Risk free rate.
β_p= Sensitivity of the portfolio return relative to the market portfolio.
$E(r_m)$= Expected return on the market portfolio.

The expected return can be divided into a risk-free component and a component for holding market risk. In general, firm-risk can further be divided into systematic and unsystematic risk (Bodie & Kane, 2020). Systematic risk is the nondiversifiable portion of risk that is related to the movement of the stock market. The unsystematic risk is the portion specific to the firm that can be diversified away. Since unsystematic risk can be diversified away, an investor will only be compensated for bearing market-related risk. The exposure to market-related risk is given by beta, which is given by the following equation:

$$\beta_p = \frac{\sigma_p * \rho_{p,m}}{\sigma_m} \tag{6}$$

Where:
β_p = The portfolios market beta.
σ_p = Standard deviation of the portfolio.
σ_m = Standard deviation of the market.
$\rho_{p,m}$ = Covariance of portfolio p and the market.

CAPM is a theoretical single factor model, stating that there is a positive linear relationship between expected stock returns and an overall market risk factor. Earlier tests done by Black and Scholes (1973) and Jensen et al. (1972) confirms this positive linear relationship. However, a lot of research has been done trying to find other risk factors that can explain stock returns (Bodie & Kane, 2020).

2.3 Arbitrage pricing theory

The Arbitrage Pricing Theory (APT) was proposed by Ross (1976) as an alternative to CAPM. He pointed to the assumptions of normality in returns and quadratic preference as being challenging to justify on theoretical grounds. In essence, APT deviates from CAPM because expected return depends on multiple factors. The expected return for k systematic factors is calculated by:

$$E(r_i) = r_f + \gamma_i \beta_{i,1} + ... + \gamma_k \beta_{i,k} \tag{7}$$

Where:

$E(r_i)$= Expected return on investment i.

r_f = Risk free rate.

γ_i= Risk premium expected from the 1-th factor

β_{i1}= Sensitivity of the investment towards the 1-th factor.

γ_k= Risk premium expected from the k-th factor

β_{ik}= Sensitivity of the investment towards the i-th factor.

APT holds when an investor is only rewarded by their factor exposure. All mispricing would be retrieved by the smart investors and arbitraged away (Ross, 1976). Multiple empirical studies have in total found hundreds of factors that can explain expected returns, however, Harvey et al. (2016) propose that most of these are likely false. Despite this finding, some factor models are still often used.

2.4 Empirical models

In this section we present some of the most popular multifactor asset pricing models. These models are often used to test whether a new factor is explained by the existing factors. Some factors are built on firm characteristics, for example: book-to-market, size, profitability, capital efficiency, liquidity, investments, cashflow, and growth (Bali et al., 2016). The factors often do not represent actual known state variables, but rather act as proxies for unknown state variables (Fama & French, 2015).

2.4.1 Fama and French three-factor model

The three-factor model was first introduced by Fama and French (1993). It is an empirical model that adds two fundamental factors to CAPM. The model is given by:

$$R_{it} - R_{ft} = a_i + \beta_{mi}(R_{mt} - R_{ft}) + \beta_{si}(SMB) + \beta_{hi}HML \tag{8}$$

Where:
R_{it} = Return on investment i in month t.
R_{mt} = Return on market portfolio in month t.
R_{ft} = Risk free rate in month t.
α_{i} = Idiosyncratic risk of investment i.
β_{mi} = Sensitivity towards the market factor.
MKTR = Return of the market portfolio minus the risk free rate.
β_{si} = Sensitivity towards the size factor
SMB = Small minus big, long small-cap and short big-cap.
β_{hi} = Sensitivity towards the the HML factor.
HML = High minus low, long high book-to-market short low book-to-market.

The model explains returns on investments by the sensitivity towards the market, a size portfolio and a value portfolio. The size portfolio is long small-cap stocks and short large-cap stocks (Fama & French, 1993). The high minus low factor captures the difference in returns related to book versus market value of equity firms. The intuition behind the size factor is that small firms have higher growth potential, while there exists a limit for large firms growth potential. For the value factor the intuition is that value stocks perform better than growth stocks. Empirically they show that this model captures variation that is otherwise not explained.

2.4.2 Carhart four-factor model

The Carhart (1997) four-factor model extends the Fama-French three-factor model with an additional factor capturing momentum. The Carhart four-factor model is given by:

$$R_{it} - R_{ft} = a_i + \beta_{mi}(R_{mt} - R_{ft}) + \beta_{si}(SMB) + \beta_{hi}HML + \beta_{momi}MOM \tag{9}$$

Where:
$\mathrm{R_{it}}$ = Return on investment i in month t.
$\mathrm{R_{mt}}$ = Return on market portfolio in month t.
$\mathrm{R_{ft}}$ = Risk free rate in month t.
α_{i} = Idiosyncratic risk of investment i.
β_{mi} = Sensitivity towards the market factor.
MKTR = Return of the market portfolio minus the risk free rate.
β_{si} = Sensitivity towards the size factor
SMB = Small minus big, long small-cap and short big-cap.
β_{hi} = Sensitivity towards the the HML factor.
HML = High minus low, long high book-to-market short low book-to-market.
β_{momi} = Sensitivity of the investment towards the the momentum factor.
MOM = Return of the momentum mimicking portfolio.

The momentum factor (MOM) captures the difference between the top 30% one year outperforming stocks and the bottom 30% one year underperforming stocks (Carhart, 1997). The intuition behind the momentum factor is that some performance trends have persisted potentially because of a delayed stock price reaction (Bali et al., 2016). Bali et al. (2016) suggests that the four-factor model is most commonly used as the benchmark for new factors.

2.4.3 Pastor and Stambaugh liquidity factor

Pástor and Stambaugh (2003) created a liquidity factor as an extension of the Fama-French three-factor model. Liquidity is by definition the ease and speed an asset can be sold at fair market value (Bodie & Kane, 2020). As a proxy for liquidity, Pástor and Stambaugh (2003) looked for price reversals caused by prior day trading volume. The four-factor model is specified as follows:

$$R_{it} - R_{ft} = a_i + \beta_{mi}(R_{mt} - R_{ft}) + \beta_{si}(SMB) + \beta_{hi}HML + \beta_{li}LIQ \quad (10)$$

Where:

R_{it} = Return on investment i in month t.

R_{mt} = Return on market portfolio in month t.

R_{ft} = Risk free rate in month t.

α_i = Idiosyncratic risk of investment i.

β_{mi} = Sensitivity towards the market factor.

MKTR = Return of the market portfolio minus the risk free rate.

β_{si} = Sensitivity towards the size factor

SMB = Small minus big, long small-cap and short big-cap.

β_{hi} = Sensitivity towards the the HML factor.

HML = High minus low, long high book-to-market short low book-to-market.

β_{li} = Sensitivity of the investment towards the the liquidity factor.

LIQ = Return of the liquidity mimicking portfolio.

Here the excess return of an asset is in this model given by the Fama-French three-factor model, but with the addition of the liquidity risk premium (LIQ) and its sensitivity.

2.4.4 Fama and French five-factor model

The shortcomings of the three-factor model regarding profitability and investment, led Fama and French (2015) to add two factors to address the incompleteness of the original model (Bali et al., 2016). From a firm valuation perspective, the dividend discount model was one of the driving forces that led them to the additional factors (Fama & French, 2015). The five-factor model is given by:

$$R_{it} - R_{ft} = a_i + \beta_{mi}(R_{mt} - R_{ft}) + \beta_{si}(SMB) + \beta_{hi}HML + \beta_{ri}RMW + \beta_{ci}CMI \quad (11)$$

Where:

R_{it} = Return on investment i in month t.

R_{mt} = Return on market portfolio in month t.

R_{ft} = Risk free rate in month t.

α_{i} = Idiosyncratic risk of investment i.

β_{mi} = Sensitivity towards the market factor.

MKTR = Return of the market portfolio minus the risk free rate.

β_{si} = Sensitivity towards the size factor

SMB = Small minus big, long small-cap and short big-cap.

β_{hi} = Sensitivity towards the the HML factor.

HML = High minus low, long high book-to-market short low book-to-market.

β_{ri} = Sensitivity of the investment towards the RMWfactor.

RMW = Robust minus weak earnings, long robust firms and short weak firms.

β_{ci} = Sensitivity of the investment towards the the CMAfactor.

CMA = Conservative minus aggressive investment, long conservative firms and short aggressive firms based on the size of investments.

Here, the RMW factor is a mimicking portfolio with the strategy of going long firms with robust earnings and short firms with weak earnings. The CMA factor is also a mimicking portfolio. This portfolio is long firms that invest conservatively and short firms that invest aggressively. Fama and French (2015) find that the five-factor model is more accurate than the three-factor model at explaining the cross-sectional return variation.

2.5 Literature review

In this part we present climate change related financial literature that forms the foundation of our thesis. We start by presenting literature on ESG and Carbon emissions as risk assessment tools. Additionally, we present literature on textual analysis for financial risk assessment as a lot of firm climate change risk disclosure is of textual form. Finally, we present recent studies that use textual analysis to quantify firm-level climate change risk.

Friede et al. (2015) find in a review study that sustainable finance has been studied since 1970. They show mixed results regarding the relationship between ESG information and corporate profitability. Although results have been mixed, Dixon-Fowler et al. (2013) show that most of the research suggests a positive relationship between corporate environmental performance and corporate financial performance. However, recent evidence by Billio et al. (2021) shows that if the ESG-scores, from different providers, are grouped from one to seven, the percentage of agreement is at best 28.2%. They further explain that this disagreement is caused by not having "cross-provider" standardization. Avramov et al. (2021) note that this disagreement is an important barrier to sustainable investing. They find that the uncertainty regarding actual sustainability is priced in the market.

Hong and Kacperczyk (2009) provide evidence of significant effects of social norms on markets by studying the behavior of what they call "sin" stocks. These "sin" stocks are publicly traded companies involved in the production of controversial good such as alcohol, tobacco, or gambling. They find that these stocks have higher expected returns than otherwise comparable stocks because the investor appetite to invest is lower for them. In a recent research by Bolton and Kacperczyk (2021), on how carbon emissions affect the cross section on US stock returns, they find that a few emissions intense industries are viewed as "sin"-investments. They also find that carbon-emissions are priced separately as a risk factor, by excluding salient industries. In a related paper, Bolton and Kacperczyk (2021) find that firms located in countries with larger energy sectors have higher emissions growth premia. The same study also finds that countries with stricter climate policies have higher carbon premiums.

The findings regarding a carbon premium are supported by Ilhan et al. (2020) who study whether stocks with higher climate change policy exposure have higher options costs for hedging strategies. Their work indicate that more carbon-intense firms have higher options costs for downside protection. They also find that negative events, for example the Paris Agreement, magnify the cost of these options. However, climate change deregulation events, such as the Trump election decreased the same options cost. Closely related is the work of Engle et al. (2020) who create a climate change news hedged portfolio. They use textual analysis on news articles to form a climate news series capturing the market reaction to climate related news coverage of events. They then use a mimicking portfolio approach to build climate change hedged portfolios that successfully hedged climate change news.

Sautner et al. (2021) use textual analysis to identify firm-level climate risk by analyzing company earnings calls. They argue that looking at the Carbon footprint of a corporation is only backward-looking and that one can not distinguish between good and bad emissions. They find that opportunity shocks have a greater impact on stock returns than regulatory or physical shocks. Further, they favor the transcripts over quarterly and annual reports because of the “greenwashing” that they state would be picked apart by the analysts asking questions. However, Kravet and Muslu (2012) test the general informativeness of the risk disclosures in the 10-K filings and find them to be informative to investors. They use a Practical Extraction and Report Language (PERL) code to parse the annual report into sentences. The code then uses a self-developed “bag-of-words” to tag sentences as risk-related. This machine-learning content analysis approach is characteristic for recent US-based research on the informativeness of the risk factors in the 10-K filing. They use this information to examine the relationship between changes in firms’ risk disclosures and changes in stock market around the disclosures. Their findings generally suggests that risk disclosure is informative. However, they observe stronger relations between industry-level risk disclosures and changes investors risk perception, which indicates that industry-level risk disclosure is more informative than firm-specific risk disclosure.

To mitigate investor uncertainty on general firm-specific risk, the Securities and Exchange Commission (SEC), in 2005, mandated firms to include a risk factor section in their 10-K filing. This risk factor section is known as item 1A, and the section includes the most significant factors that makes the firm speculative or risky. Campbell et al. (2014) investigates whether the disclosed risk factors in item 1A affects the firms’ risk level, and whether risk information is reflected in systematic risk, idiosyncratic risk, information asymmetry, and firm value. They use a similar approach as Kravet and Muslu (2012) to identify risk information and classify risk-related statement into different groups; financial, systematic, idiosyncratic, legal and regulatory, or tax. Their findings show that firms facing greater risk disclose more risk factors. They also find that the information in the risk factor disclosures is reflected in systematic risk, idiosyncratic risk, information asymmetry, and firm value. Abraham and Cox (2007) finds that corporate risk reporting is negatively related to share-ownership by long-term institutions. Their study therefore suggests that institutional investors do prefer firms with a lower level of risk disclosure. Their research suggests that the disclosures appear to be firm-specific and useful to investors, and therefore supports the SEC's decision to mandate specific risk factor disclosures.

In a more recent study Berkman et al. (2021) create a climate risk score based on firm-specific climate change disclosures in the 10-k filing. They argue that companies are required to disclose climate related risk in Item 1A of the 10-k filing. These parts where analyzed using a keyword and phrases-based approach to quantify climate change risk. They find that their risk metric, to a greater extent, can explain firm level valuation compared to other climate risk measurements. Similarly, Kölbel et al. (2021b) also use a textual analysis on the climate change risk disclosures in the 10-k reports. To the contrary, Kölbel et al. (2021b) use a more sophisticated textual analysis method. They use a BERT (Bidirectional Encoder Representations from Transformers) model, which is a state-of-the-art Natural Language Processing Technique (NLP) that can capture the actual context of sentences versus just combinations of keywords. Kölbel et al. (2021b) tested if credit default swaps (CDS) are priced differently in regards to their measure of firms climate change risk. They found that on average disclosing transition risk increases the CDS spread and noted that it was especially true for the time period after the Paris Agreement. The opposite was true for firms' disclosure of physical risk, which decreased the spreads.

As a robustness test, Kölbel et al. (2021b) repeated the analysis using Carbon emission and data from both Sautner et al. (2021) and Berkman et al. (2021). The findings did not replicate using any of the alternative measurements. Kölbel et al. (2021b) attribute their findings to the fact that the BERT model gives a more precise measurement than the keyword based method and that the 10-k reports are more standardized than the earnings calls. The hypothesis of Kölbel et al. (2021b), regarding the bad data quality generated by the keyword based approaches, are further validated by Varini et al. (2020), who show that even a simple BERT model, like the one used by Kölbel et al. (2021b), significantly outperform keyword based approaches. Varini et al. (2020) suggest that if one wants to use NLP techniques to generate a proxy for climate change risk it must capture the essence of what is being discussed with at least the precision of a simple BERT model.

Further, it is important to assess how risk disclosure affects risk premiums. Damodaran (2020) states that more precise information should lead to a lower equity risk premium because the uncertainty about future earnings and cash flows is decreased. One issue regarding precise information in the 10-k filing, brought up by Kölbel et al. (2021b), is that the disclosures are often boilerplate and don't provide any critical information. But in a literature review of risk reporting, Elshandidy et al. (2018) find that most papers that analyzed 10-K filings, find that risk disclosure is informative and that the disclosure leads to an increase in risk perception. Beretta and Bozzolan (2004) investigate the quality of risk disclosure. They find no relationship with either size or industry, but regarding the quantity of risk disclosure, there is a positive relationship with firm size, but no relationship with industry. Linsley and Shrives (2006) finds a significant association between the number of risk disclosures and level of environmental risk. The work of Beretta and Bozzolan (2004) and Linsley and Shrives (2006) makes it natural to assume that large firms disclose more climate related risk than small firms.

3 Methods

We start this section with a brief introduction to the methods of choice for empirical asset-pricing, and our model specification. We end the section with a time-series approach to test whether the potential risk premiums are driven by known risk factors.

3.1 Empirical asset pricing

To examine a risk factor in the cross-section of stock returns, Bali et al. (2016) presents two original methods: The most common approach is the mimicking portfolio method by Fama and French (1993). The approach consists of grouping firms into deciles or quantiles, based on the factor exposure of the firms in the sample. Then a long short zero investment portfolio is created by going long the highest group and short the lowest. The factor risk premium is then the difference in return between the two portfolios. One drawback with this approach is the difficulty of controlling for large sets of control variables (Bali et al., 2016). An approach that does not have this disadvantage is the Fama and MacBeth (1973) approach, here the regression is done in two steps: 1) Run a cross-sectional regression at each point in time where the dependent variable is regressed against the independent variables, 2) Analyze if the time series of coefficients from step one is on average different from zero (Bali et al., 2016). However, this method requires that we make the assumption that the relationship is of linear nature (Bali et al., 2016). A general assumption in finance is that risk and return have a positive linear relationship. Therefore, if disclosure of risk is seen as risk by investors, the relationship between the disclosure of climate change risk and returns should be expected to be linear. Additionally, isolating the risk premium by including multiple control variables will make our results more robust.

3.2 Model Specification

Based on the literature regarding pricing climate change risk in the cross-section of stock returns, we find that one often used method is a pooled panel regression with time and industry fixed effects (Bolton & Kacperczyk (2021), Brandon et al. (2021)). Brandon et al. (2021) describe a pooled panel regression with month-industry fixed effects as conceptually similar to a Fama and MacBeth (1973) type of regression with industry dummies at each time. Time fixed effects are included to capture the systematic differences that occur over time. For example, if one month has greater returns than another month, the time fixed effects will capture this difference so that this effect is not falsely attributed to unrelated factors. The industry fixed effects capture systematic differences related to the cyclical nature of industries. Brandon et al. (2021) state that they include industry fixed effects because of a relatively short sample period and sector variation regarding their factor of interest. In our case, to test whether regulatory disclosure affects the cross-section of US stock returns, we run a cross-sectional regression with time and industry fixed effects using pooled OLS with the following model specification:

$$R_{i,t} = \alpha_0 + \alpha_1 CCRISK_{i,t} + \alpha_3 Controls_{i,t} + \mu_t + \epsilon_{i,t} \tag{12}$$

where *Ri,t* is the monthly return of company i in month t and CCRISK is eihter physical risk, transitional risk or total risk, which we test individually. Controls is a set of control variables that are firm specific and that have been shown to impact stock returns. Bali et al. (2016) for example suggest a strong negative relationship between firm size and stock returns, and a strong positive relationship between book-to-market and stock returns. We partially follow the specifications used by Brandon et al. (2021) and Bolton and Kacperczyk (2021), based on the availability of data and because of the limitations of time. We choose Pooled OLS with time and industry fixed effects and standard errors clustered at firm and year because of Petersen (2008) findings, that under similar conditions, this approach should create unbiased standard errors.

We include the following control variables: The first control variable is firm size (log(marketcap)). This variable is calculated by the natural logarithm of firm i's market capitalization (the share price times shares outstanding) at the end of each month t. The second control variable is the book-to-market (bmi,t), which is the firm i's book value of equity divided by its market capitalization at the end of year t. Our third control variable is gross profit (gross_profit), which is sales minus cost of goods sold divided by total assets. Our fourth control variable is sales growth rate (salesgr), which is firm i's annual dollar change in sales divided by last month's market capitalization. The fifth control variable is market beta (marketbeta), which is the sensitivity of firm-spesific returns to market wide returns of firm i in year t. We use daily excess returns in a rolling window regression with 250 days against the return of the market (represented by the market factor from Ken French's website), this should be equivalent to the CAPM beta. For the rolling regression we require at least 200 days of observation. momt11, which is our sixt control variable, represents the momentum of firm i's 12 month prior performance. We calculate momentum by taking the cumulative monthly return for the 11 most recent months leading up to month t-1.

This specification excludes some control variables that Brandon et al. (2021) and Bolton and Kacperczyk (2021) used. For example, we did not include total volatility. We therefore note that we potentially omit important variables, meaning that we could have omitted variable bias making our findings unreliable. However, Harvey et al. (2016) argues that many of the claimed risk factors in financial economics are likely false, which means that the excluded variables where not necessarily important. Additionally, the model specifications used by Brandon et al. (2021) and Bolton and Kacperczyk (2021) are not identical and therefore we where forced to omit some variables from either regardless of constraints.

3.3 Robustness regarding specific industries driving results

Bolton and Kacperczyk (2021) point at the industries: Utilities, Oil and gas and transportation and refer to them as salient industries because they produce the most significant fraction of emissions. Similarly, these industries are expected to disclose the highest transition risk, and could be the main drivers of results. Therefore, to make sure that our results are not purely driven by these industries, we exclude them and rerun the regressions. Since it is mandatory for firms to disclose all known risks, that can significantly affect operations, in Item 1A. One would expect firms that operate in industries where climate change risk is of material matter to disclose disproportionately more than those in non-material industries. We therefore repeat the exclusion process in regards to materiality for additional robustness. We follow Kölbel et al. (2021b) for the industry materiality assessment. Kölbel et al. (2021b) applied an adjusted version of

Matsumura et al. (2018) materiality assessment procedure. To consider climate change as a material risk towards an industry, they require four out of seven general issues to be of concern in the SASB Materiality Map®. For this project, we have licensed the SASB Standards from the Value Reporting Foundation.

3.4 Time-series test

The next step is to assess if the risk premium related to the disclosure climate change risk is already explained by the known risk factors. To do this we extract the risk premiums by running only the first stage of the cross-sectional Fama and MacBeth (1973)- regression. For this calculation we create a function that runs the cross-sectional regression at each year-month and that extracts only the coefficient for our risk metric. To test whether this method actually yields the same results as a standard Fama and MacBeth (1973) regression, we simply compare the mean of the extracted risk premium with the coefficients found using the pmg() function of the plm package with reversed panel indexes. The last step is to test whether the risk premium is related to any of the known risk factors. This is done by a time series regression where the dependent variable is the extracted risk premiums and the independent variables are the known risk factors. For the independent risk factors we use the five factor model of Fama and French (2015) (Mkt.RF, SMB, HML, RMW, CMA, and MOM) from Ken-French's website and the Pastòr and Stambaugh LIQ factor from Stambaugh's website.

4 Data

In this section, we start by presenting the main dataset for the firm-level climate change risk metric. We use a sample period of 11 years, starting in january 2010 and ending in december 2020. Next, we present return and financial data from FactSet and the data used in the time-series test. For industry classification we use the SASB Sustainable Industry Classification System® (SICS®). We end this section with some important data-wrangling.

4.1 Data on disclosures of climate change risk

We use the publicly available data on climate change risk disclosures from Kölbel et al. (2021a). We chose the extended dataset for US firms with sentence level data. The dataset includes 1134 firms with a total of 13 million observations. These observations are sentences or sentence-pairs, from Item 1A in the 10-k filings, that Kölbel et al. (2021b) classified using a finetuned BERT algorithm. As noted Kölbel et al. (2021b), using the disclosures from Item 1A is advantageous because this section is dedicated to the mandatory disclosures of risk. Kölbel et al. (2021b) structured the algorithms' topic classification to differentiate between physical climate change and transitional climate change. Each 10-k filing is identified by the firm's ticker and fiscal year end date. The sentence classification is structured by three topics and the corresponding probability given by the algorithm. These topics are: general risk, transitional climate change risk, and physical climate change risk. We follow Kölbel et al. (2021b) and set the probability threshold at 0.8, meaning that the algorithm needs to be at least 80 % certain of the topic. The sentences related to climate change will have a value of one and zero otherwise.

To quantify firm-level climate change risk, we follow Kölbel et al. (2021b), who define the risk scores as the amount of climate relevant sentences divided by the total amount of sentences for each annual report. We call this the "Rate of disclosure" and it is given by:

$$Rate_{it} = \frac{\sum_{i=1}^{n_{it}} S_{it}}{n_{it}} \tag{13}$$

here the "Rate of disclosure" for each firm i, at each fiscal year end t, is calculated by the sum of all climate change sentences *Sit* divided by the total amount of sentences. Alternatively, Linsley and Shrives (2006) find a significant positive relationship between the quantity of disclosure and the level of environmental risk. Therefore, the quantity of climate risk disclosures could be important to investors. We calculate the quantity of disclosure by:

$$Quantity_{it} = \sum_{i=1}^{n_{it}} S_{it} \tag{14}$$

here the "Quantity of disclosure" is given by the sum of all sentences *Sit*, for each firm i at each fiscal year end t. Operationally, for these calculations we use the *data.table R-package* by Dowle et al. (2019). We calculate the rate and quantity for physical, transitional and total climate change risk. Total risk is the sum of the transitional and physical risk. The aggregation led to 83 472 risk risk scores, meaning that each risk metric has 13 912 observations. The total number of unique firms was unchanged, indicating that each Item 1A, on average, contains 100 sentences.

Figure 1 shows the number of firms included each year. We follow Kölbel et al. (2021b) and exclude the dates before 2010 because of a change in the regulatory reporting requirements regarding climate change risk disclosures. Additionally, Figure 2 shows that there was an increase in reported transition risk following the regulatory change in 2010. Regarding the Paris Agreement we observe an increase in the amount of disclosed climate change risk. From Figure 2 we observe that total risk is mainly driven by transition risk, but since 2015, physical risk has been the main contributor. The average quantity of transition risk has been stable since 2015 while the rate has been declining. This indicates that the amount of other risk disclosure has increased.

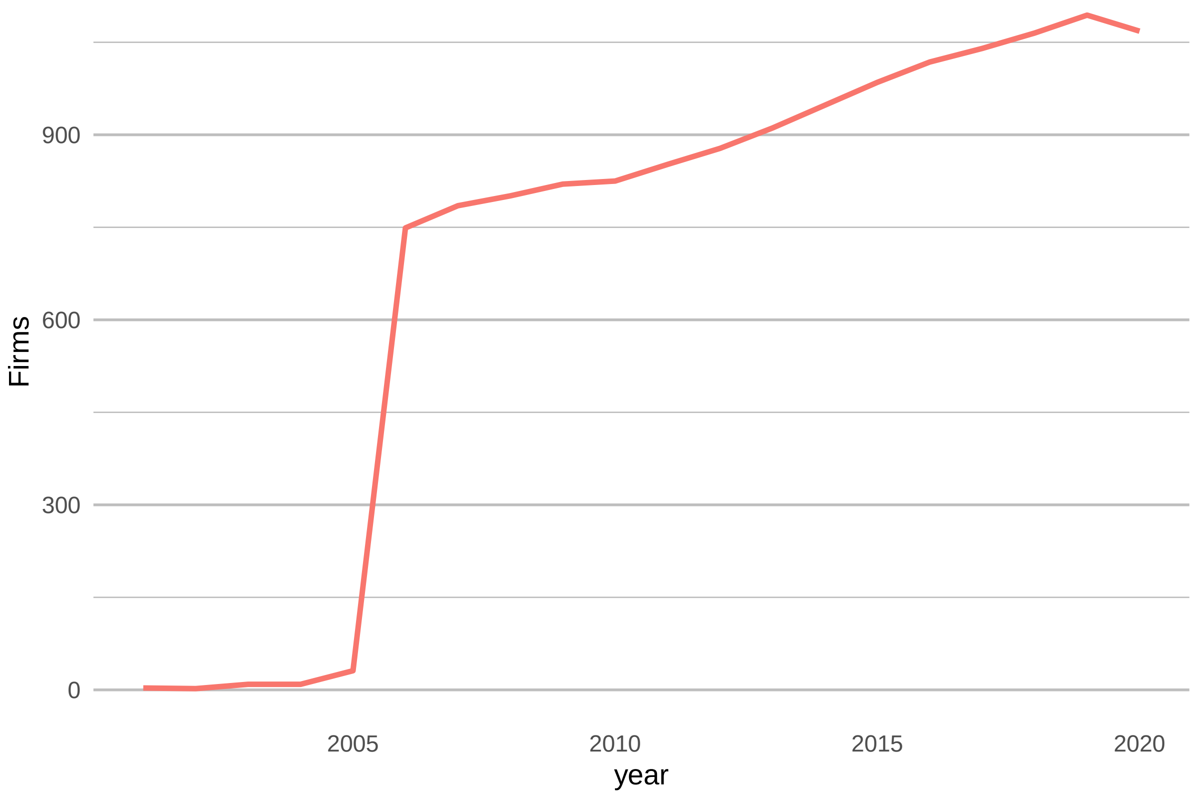

Figure 1: Number of firm year observations.
The data source is @datakolbel2021ask. We use fiscal year end + 90 days to aggregate the number of firms present each year.

Figure 2: Disclosure metrics time series summary.
The data source is @datakolbel2021ask and the data has dates ranging from 2000 to 2020. We use the first date that information is public to aggregate the number of firms present each year.

4.1.1 Outlier analysis and dataset cleaning

The extended dataset from Kölbel et al. (2021a) is raw data and we therefore need to identify where the data collection procedure led to false observations. For the outlier analysis we create *baselength*, which is the total number of sentences/sentence-pairs for each annual filing. Next, we take a random sample test of the filings with the lowest *baselength* and investigate if it matches the actual amount.

We first we looked into Item 1A of US Bancorp (2017) Form 10-K. Here, they disclose the following:

"Information in response to this Item 1A can be found in the 2017 Annual Report on pages 146 to 156 under the heading"Risk Factors." That information is incorporated into this report by reference." (U.S. Bancorp (2017), p. 15) Here, the real disclosure is made not through the two sentences, but rather on pages 146 to 156. The classification was made on the wrong sentences, wich gives a misleading result. We find multiple instances with similar discrepancies and some examples are given below. For example: Huntington Ingalls Industries Inc. had an average baselength of 168 while 2015 had 2 observations. We looked into a handful of their 10-k filings and did not find that the Huntington Ingalls Industries Inc. (2015) filing had a notably lower amount of sentences.

We observe the a similar pattern with Ball Corporation (2015) Form 10-K where only one observation is detected in our dataset, while the filing includes substantially more. The final firm we looked into is EOG Resources (2014) We find that their Item 1As from 2011 to 2014 on average span over 8 full pages of disclosures. The same reports have *baselengths* ranging from 10 to 12 sentences. We see it as unrealistic that there could be less than 40 sentences on 8 pages. Taylor et al. (2010) find that all firms have to report on at least 13 financial risk items. We argue that a material risk disclosure of one item would on average be one sentence long. We therefore set the minimum required baselength to 13, and exclude firms that at any point had a baselength lower than 13. This is a conservative approach that excludes 133 firms. However, based on our random sample test, we believe that this strict exclusion criteria is necessary. Before this exclusion we winsorize our climate change metrics at 2.5% to limit the effect of outliers.

Table 1: Outlier identification.

date	ticker	baselength	date	ticker	baselength
2010-12-31	USB	2	2011-12-31	HII	209
2011-12-31	USB	2	2012-12-31	HII	217
2012-12-31	USB	2	2013-12-31	HII	206
2013-12-31	USB	2	2014-12-31	HII	195
2014-12-31	USB	2	2015-12-31	HII	2
2015-12-31	USB	2	2016-12-31	HII	183
2016-12-31	USB	2	2017-12-31	HII	171
2017-12-31	USB	2	2018-12-31	HII	166
2018-12-31	USB	1	2019-12-31	HII	164
date	ticker	baselength	date	ticker	baselength
2010-12-31	EOG	66	2010-12-31	BLL	62
2011-12-30	EOG	10	2011-12-31	BLL	71
2012-12-31	EOG	10	2012-12-31	BLL	82
2013-12-31	EOG	11	2013-12-31	BLL	81
2014-12-31	EOG	12	2014-12-31	BLL	1
2015-12-31	EOG	19	2015-12-31	BLL	1
2016-12-31	EOG	17	2016-12-31	BLL	100
2017-12-31	EOG	16	2017-12-31	BLL	101
2018-12-31	EOG	17	2018-12-31	BLL	105

4.2 Return and financial data

We use FactSet's return data and fundamental financial data. FactSet is seen as a reputable source for return data on US firms and other markets and is survivorship bias free. We wish to note here that although our return data is survivorship bias free, we cannot ignore the possibility that the sample obtained from Kölbel et al. (2021a) is free of said bias, although we do not believe this to be the case. We use the *data.table R-package* by Dowle et al. (2019) to aggregate the daily returns, from FactSet, into monthly returns by calculating the cumulative product of the daily returns for each month. Next, to limit the impact of outliers in returns we follow Bolton and Kacperczyk (2021) and remove observations where the monthly return is greater than 100%. Additionally, we winsorize gross profit, sales growth rate, momentum and book to market at 2.5%. For data on the traditional risk factors, we use the publicly available return series from Ken French's website for the Fama-French 5 factor model and the monthly momentum factor. Additionally, we download the liquidity factor from Stambaugh's website.

4.3 Industry classification

Li et al. (2020) finds that the GICS8 and the Fama French 48 (FF48) industry classifications generate consistent performance for specific industry portfolios. Kölbel et al. (2021b) chose to use the SASB SICS® and argues that it might be beneficial as industries are defined not only on financials, but also on sustainability similarities. Similarly, Bolton and Kacperczyk (2021) use a vendor specific climate impact sector classification. Given the findings from Li et al. (2020), we follow Kölbel et al. (2021b) and rely on the SASB SICS® as we did not directly have access to SIC codes. In contrast to Kölbel et al. (2021b) we chose the SICS® Codified Sub-Sector classification, with 38 groupings, because it is the closes in number of groupings to the 48 industry classification of Fama French. In Table 2 we show the distribution of firms given the SICS® Codified Sub-Sector industry classification.

To illustrate industry variations, we plot the SICS® sector average scores and amount of sentences in Figures 3 and 4. The figure shows that the disclosure of climate change risk is rather sector dependent. Physical risk seems to be less skewed while both transition and total risk are skewed towards the non-renewable industries. One surprising find is that the "Renewable Resources and Alternative Energies" sector has a high rate of disclosure of climate change transition risk, which in essence does not make sense. On the other hand, in Item 1A, firms disclose all risks that are of material matter. This includes the risk of a decrease in renewable subsidies, sanctions on solar panel imports, tightened regulation on for example wind-power generation and many more. For example, we believe that the following sentence: *«An increased global supply of PV modules has caused and may continue to cause structural imbalances in which global PV module supply exceeds demand, which could have a material adverse effect on our business, financial condition, and results of operations.»* (First Solar (2019), p. 11), was identified by the BERT model as a sentence with transitional climate change topic. Here, they are simply talking about pricing pressure related to supply and demand and not transition risk. As the scores on average for this industry are high and most likely false they can introduce bias into our results. Interestingly, the industry based materiality assessment also includes the renewable energy sector, meaning that they are excluded when controlling for materiality.

Table 2: SICS Codified Sub-Sector

SICS Code	SICS Codified Sub-Sector	firms
CG.1	Apparel & Textiles	12
CG.2	Consumer Discretionary Products	19
CG.3	Consumer Goods Retail	42
EM.2	Construction Materials	6
EM.3	Metals & Mining	11
EM.4	Oil & Gas	34
FB.1	Food	19
FB.2	Beverages	8
FB.3	Food & Beverage Retail	7
FB.4	Restaurants	11
FB.5	Tobacco	1
FN.1	Capital Markets	27
FN.2	Corporate & Retail Banking	66
FN.3	Insurance	38
HC.1	Biotechnology & Pharmaceuticals	47
HC.2	Health Care Retail	2
HC.3	Health Care Providers	25
HC.4	Medical Technology	41
IF.1	Utilities	40
IF.2	Infrastructure	9
IF.3	Real Estate	84
IF.4	Waste Management	4
RR.1	Alternative Energy	5
RR.2	Forestry & Paper	3
RT.1	Industrials	80
RT.2	Chemicals	32
SV.1	Media	15
SV.2	Hospitality & Recreation	22
SV.3	Consumer Services	31
TC.1	Technology	131
TC.2	Internet Media & Services	15
TC.3	Semiconductors	29
TC.4	Telecommunications	8
TR.1	Air Transportation	10
TR.2	Automobiles	13
TR.3	Marine Transportation	2
TR.4	Land Transportation	9
Total	-	958

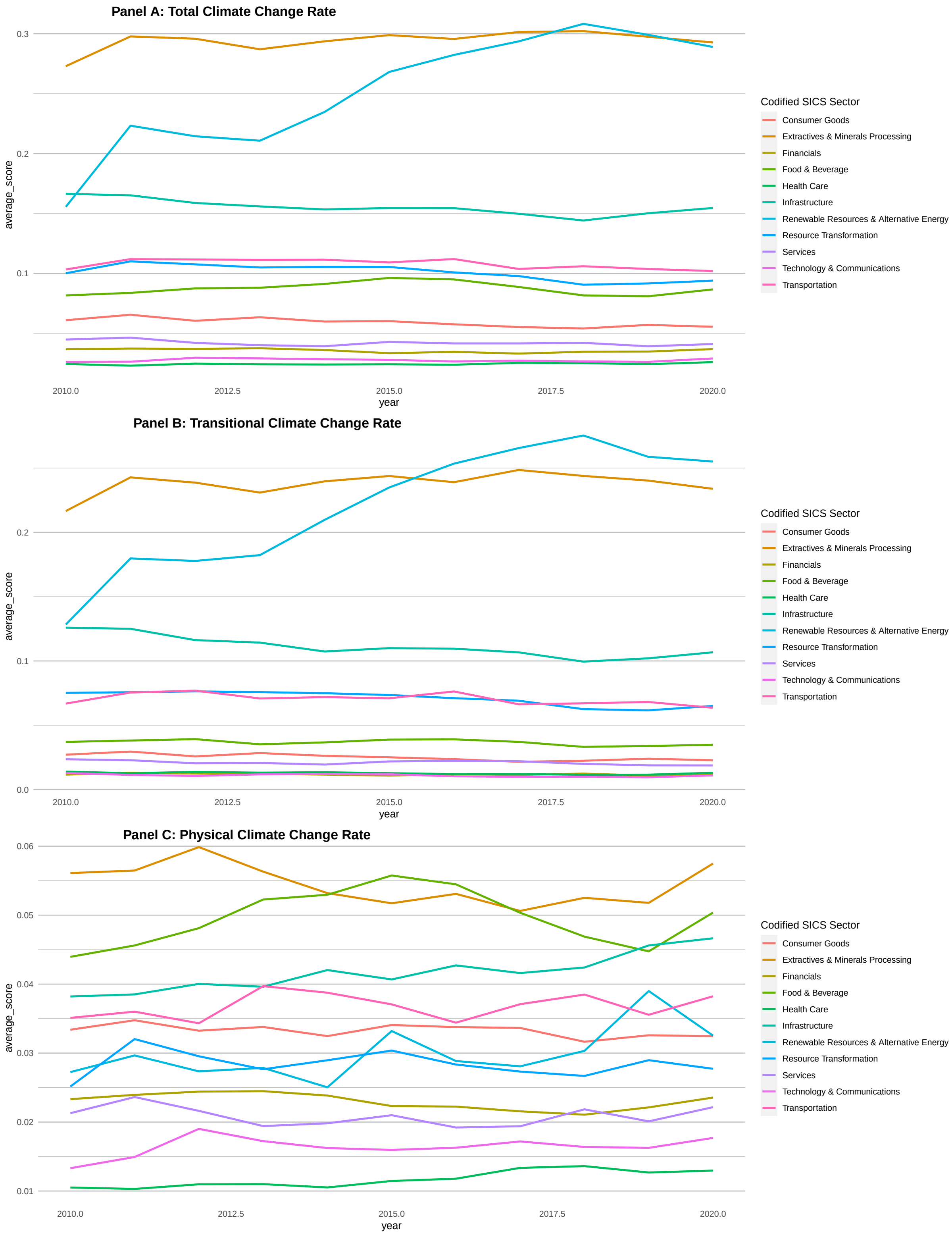

Figure 3: Sector average rate of disclosure.
For industry classification we use the SICS® Sector classification from SASB.

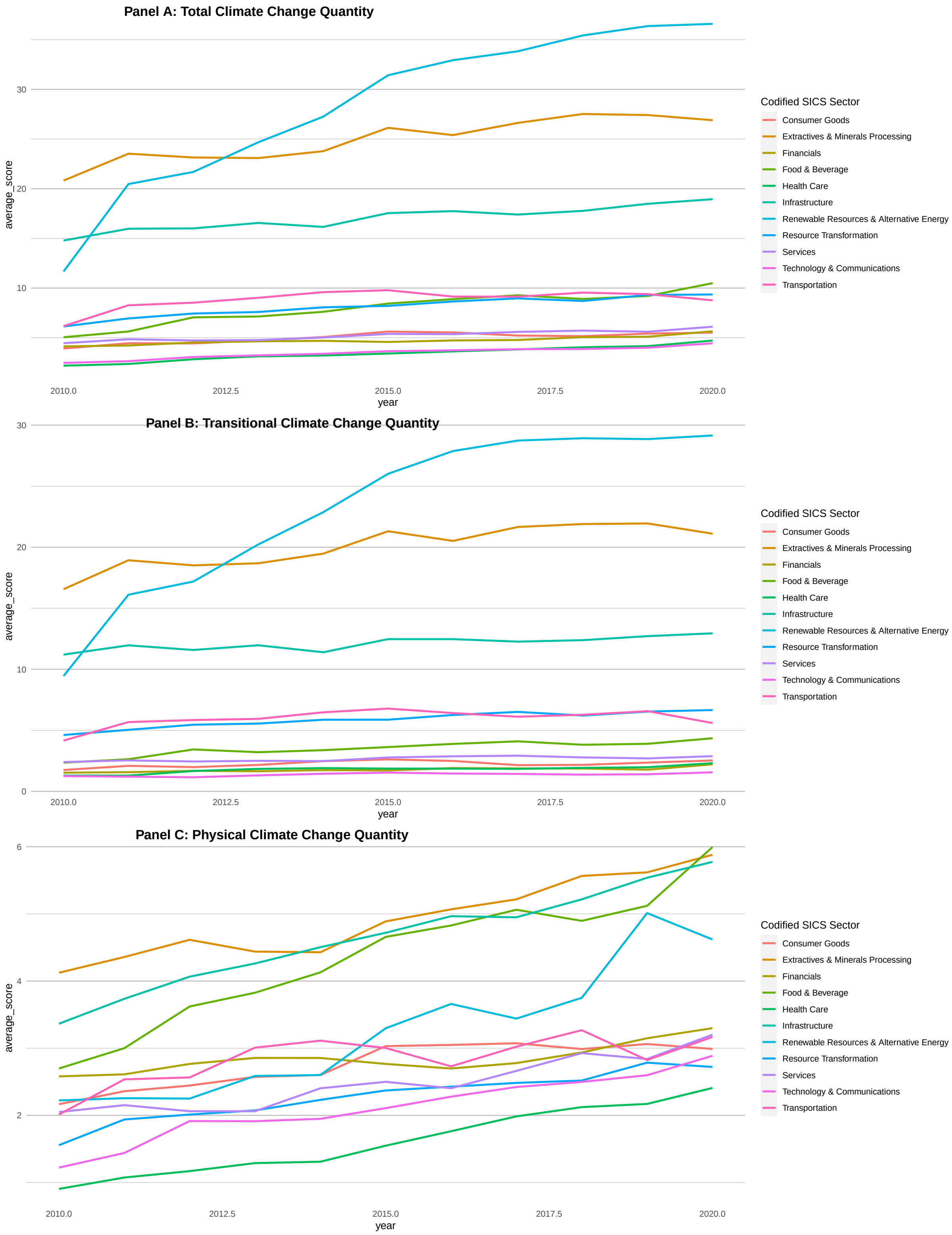

Figure 4: Sector average quantity of disclosure.
For industry classification we use the SICS® Sector classification from SASB.

Table 3: Summary statistics. This table reports the summary statistics of all the variables that where used for the analysis. Our sample period is 2010 to 2020.

	n	mean	sd	skew	kurtosis
Climate risk variables					
wriskphys	103406	0.029	0.030	1.409	1.630
wrisktrans	103406	0.054	0.085	2.181	4.166
wrisktot	103406	0.084	0.102	1.855	2.816
wsentphys	103406	3.001	3.027	1.296	1.215
wsenttrans	103406	5.425	8.484	2.333	5.021
wsenttot	103406	8.504	10.502	2.098	4.075
Financials					
monthly_return	109746	1.566	9.596	0.453	6.360
marketbeta	107362	1.082	0.411	0.250	4.878
marketcap	109746	8.840	1.305	0.376	0.815
wmomt11	106961	0.173	0.347	1.644	6.281
wbm	102086	0.441	0.303	0.950	0.369
winvesta	103126	3.807	3.861	1.603	2.418
wgross_profit	90498	0.264	0.191	0.901	0.200
wsalesgr	103332	0.029	0.175	-0.287	15.817
Mixed					
Y15	109746	0.495	0.500	0.022	-2.000
TMateriality	109746	0.182	0.386	1.647	0.714
PMateriality	109746	0.157	0.364	1.887	1.562

4.4 Combining the datasets

We merged the main climate change risk dataset with the fundamental data from FactSet based on CUSIP and fiscal year end. Further, we merged the combined dataset with the monthly return dataset on the stable identifier FSYMID and public date. We chose this order because Item 1A is available to investors at the same time as the fundamental data. We used the last observation carried forward to fill observations between filings because date was a merging criteria. The last merging added SICS® industry classification and materiality dummies. We report the descriptive statistics of the final dataset in Table 3.

Our summary statistcs table shows the variables used in the cross-sectional regressions. In Table 3 variables starting with "w" are winsozired at 2.5%. **Climate risk variables** are estimated using the raw data from Kölbel et al. (2021a). Here the variables with "risk" represent the rate of disclosure while "sent" represents the quantity of disclosure. **Financial** are variables used in the cross-sectional regressions.

monthly_return is the monthly return; marketbeta is the CAPM beta on daily returns; *marketcap* is log(marketcap)(log only applies here); *wmomt11* is the monthly cumulative return; *wbm* is book to market; *winvesta* is CAPEX divided by total assets; *wgross_profit* is gross profit divided by total assets; *wsalesgr* is the year over year change in sales divided by marketcap. **Mixed** are miscellaneous variables. *Y15* is a dummy variable used to sort pre and post Paris Agreement; *TMateriality* is a dummy for industry based materiality assessment based on the Kölbel et al. (2021b) adjusted Matsumura et al. (2018) procedure using the SASB Materiality Map®.

Table 3 shows that the average firm in our sample discloses 8.5 climate related sentences in Item 1A which equals to 2.9% of all Item 1A disclosures. Of these, 5.4 sentences are about transition risk and 3 sentences about physical climate change risk.

5 Results

In this section we begin by investigating how firm characteristics relate to the disclosure of climate change risk. Next, we analyze if there exists a climate change risk disclosure premium in the cross-section of returns. Thereafter, we test whether this premium is related to well-known risk factors using a time-series regression. Finally, we investigate if the Paris Agreement had an effect on the size of the risk premium.

5.1 Determinants of climate change risk disclosure

Firstly, we relate the firm characteristics to the rate of disclosure before turning to the quantity of disclosure. Bolton and Kacperczyk (2021) note that there exists little research on what firm characteristics determine the level of carbon emissions. For disclosures in general, Beretta and Bozzolan (2004) found a positive relationship between the amount of disclosure and firm size, but no relationship with industry. Partly following Bolton and Kacperczyk (2021), we include a subset of the control-variables that we use in the cross-sectional regression. This subset of firm-level variables consists of: log(marketcap), wbm, wgross_profit, winvesta and wsalesgr.

Table 4:
Determinants of disclosure rate.
Sample period 2010 to 2020. Dependent variables are the disclosure rates of climate change risk. Regression includes year-month and industry fixed effects with standard errors clustered at the firm level and year. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

	wriskphys		wrisktrans		wrisktot	
	(1)	(2)	(3)	(4)	(5)	(6)
log(marketcap)	0.003***	0.001**	0.005**	0.000	0.007**	0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
wbm	0.012***	-0.000	0.043***	0.008	0.054***	0.005
	(0.003)	(0.003)	(0.011)	(0.006)	(0.013)	(0.007)
wgross_profit	-0.013**	0.012*	-0.144***	-0.045***	-0.157***	-0.030**
	(0.006)	(0.005)	(0.013)	(0.009)	(0.016)	(0.012)
winvesta	0.002***	0.000	0.009***	0.003***	0.011***	0.003***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
wsalesgr	0.002	0.000	-0.008	0.008	-0.007	0.008
	(0.002)	(0.002)	(0.012)	(0.005)	(0.013)	(0.006)
Observations	88,945	88,945	88,945	88,945	88,945	88,945
R^2	0.1020	0.3617	0.3027	0.7287	0.2976	0.7271
Within R^2	0.1016	0.0123	0.3015	0.0494	0.2968	0.0348
Industry		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes

5.1.1 Determinants of the rate of disclosure

Having defined the rate of disclosure as the percentage of sentences attributed to climate change risk, we now relate to it the subset of firm characteristics. We run a cross-sectional regression using Pooled OLS with time and industry fixed effects and standard errors clustered at the firm-year following Bolton and Kacperczyk (2021). The result of this regression has been summarized in Table 4, with rate of disclosure as the dependent variable. The R-Squared values show that the firm's characteristics to a lesser extent explain the variation in the rate of disclosed physical risk compared to transitional and total risk. Additionally, the R-Squared values increase when adjusting for industry fixed effects, showing that the rate of disclosure is industry dependent. With the same adjustment, we observe a significant positive relationship between the rate of disclosure and marketcap (log(marketcap)), whereas the same relationship to *gross_profit* is only marginally significant. Furthermore, we find that transitional risk and total risk are both negatively related to *gross_profit* and positively related to *investa*.

The moderate relation between physical risk disclosure and firm characteristics may be explained due to geographical location being the main driver of a firm's physical climate change risk. We argue this because Giglio et al. (2021) suggests that a firm's exposure to physical climate change risk can vary even in the same narrow geography. The positive relation between firm size and physical risk can be attributed to a larger supply chain, which increases the potential vulnerability towards extreme weather events. The negative relationship between transition risk and gross profit could be due to tightened regulations for emissions, which in turn leads to higher costs of goods sold. The same assumption can be made for the positive relation between transition risk and investment rate, where firms that face tightened regulations could be investing into emission reducing technologies. We find that the industry fixed effects increase the models explanatory power substantially, this indicates that the rate of disclosure is rather industry dependent. This corresponds with the sector heterogeneity observed in Figure 3 and Figure 4.

5.1.2 Determinants of the quantity of disclosure

Having investigated the relationship between the rate of disclosure and the firm characteristics we rerun the regression using the quantity of disclosure as the dependent variable. As previously defined, the quantity of disclosure is simply the number of climate change risk sentences that a firm discloses. The results of this regression are summarized in Table 5 and are similar to those of the disclosure rate regarding industry dependence and the R-Squared discrepancy between physical and transitional/total risk. In contrast to the rate of disclosure, the quantity of disclosure is positively related to the sales growth-rate for all dependent variables when adjusting for industry fixed effects. This applies to the rate of investments as well, although only marginally significant for physical risk. Furthermore, we find that firm size and gross profit is negatively related to the quantity of transitional and total risk disclosure.

The negative relationship between gross profit and the quantity of transitional and total risk disclosure can be due to the aforementioned increased costs of pollution. Another possible explanation, which applies to the rate of disclosure as well, is increased competition from subsidized projects such as low-cost renewable energy. Our findings regarding the significant positive relationship between sales growth and the quantity of physical climate change risk disclosure, could be explained by an expanding or more fragile supply chain. Alternatively, one could argue that a firm in a growth stage is less financially robust against disruptions by extreme weather events. The significant negative relation between market cap and the quantity of transition and total risk disclosure, can be attributed to the equity being valued lower because investors demand a higher risk premium. We argue this because Linsley and Shrives (2006) find a positive relationship between the amount of risk disclosures and environmental risk.

Table 5:
Determinants of disclosure quantity.
Sample period 2010 to 2020. Dependent variables are the disclosure quantities of climate change risk. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

	wsentphys		wsenttrans		wsenttot	
	(1)	(2)	(3)	(4)	(5)	(6)
log(marketcap)	0.059	-0.102	0.000	-0.362**	0.045	-0.473**
	(0.071)	(0.059)	(0.185)	(0.131)	(0.232)	(0.168)
wbm	1.056**	-0.000	3.810***	0.306	4.932***	0.324
	(0.343)	(0.302)	(1.102)	(0.691)	(1.299)	(0.867)
wgross_profit	-2.684***	-0.441	-14.924***	-5.365***	-17.822***	-5.844***
	(0.520)	(0.502)	(1.305)	(1.121)	(1.610)	(1.422)
winvesta	0.161***	0.039*	0.797***	0.247***	0.966***	0.287***
	(0.023)	(0.020)	(0.080)	(0.052)	(0.095)	(0.065)
wsalesgr	0.650**	0.652**	0.581	1.999**	1.307	2.700**
	(0.285)	(0.255)	(1.103)	(0.732)	(1.244)	(0.896)
Observations	88,945	88,945	88,945	88,945	88,945	88,945
R^2	0.1132	0.3207	0.2613	0.6174	0.2563	0.5977
Within R^2	0.0939	0.0073	0.2601	0.0441	0.2525	0.0383
Industry		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes

5.2 Evidence on cross-sectional return

In this section, we explore if the cross-sectional return is affected by the disclosure of climate change risk, in an attempt to determine if investors care about this disclosure. We run pooled OLS regressions using the following cross-sectional regression model:

$$R_{i,t} = a_0 + \alpha_1 CCRISK + \alpha_3 Controls + \mu_t, \tag{15}$$

where *Ri,t* measures the stock return of firm i in month t and *CCRISK* individually represents physical risk, transitional risk, and total risk. The *Controls* consist of firm-characteristic variables known to predict returns, a detailed explanation is given in Methods. We include year-month and industry fixed effects and cluster the standard errors at firm-year, following Bolton and Kacperczyk (2021). By investigating if there exists a risk premium related to the disclosure rate or quantity, we get closer to accepting or rejecting our initial proposition. We note that under these model specifications we get a significant positive relationship between firm size and stock returns, which is in conjunction with the Fama and French (1993) small minus big factor. We were not able to determine if this was due to our model being misspecified or due to the sample period, but believe the latter to be true as this significance was only observed in the post Paris Agreement period (see Table 11).

5.2.1 Disclosure rate risk premium

The results in Table 6 show that the rate of disclosure does not affect returns when controlling for industry fixed effects. On the contrary, when industry fixed effects are not controlled for, we observe a significant risk premium related to the rate of disclosed transitional and total risk, indicating its relation to industry-specific effects rather than the rate of disclosure itself. Whereas, physical climate change risk disclosure remains equally insignificant.

Our results indicate that investors do not pay attention to the rate of climate change risk disclosure. These findings partly support our null hypothesis, which states that this information is unimportant to investors. Our results are somewhat in contrast

Table 6:
Disclosure rate and stock returns.
Sample period 2010 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

	monthly_return					
	(1)	(2)	(3)	(4)	(5)	(6)
wriskphys	-3.38	-0.092				
	(2.25)	(1.06)				
wrisktrans			-2.18**	-0.607		
			(0.887)	(0.759)		
wrisktot					-1.80**	-0.379
					(0.761)	(0.526)
marketbeta	0.649*	0.640*	0.684*	0.646*	0.664*	0.643*
	(0.339)	(0.319)	(0.333)	(0.319)	(0.336)	(0.318)
wgross_profit	0.935**	0.465*	0.673*	0.442	0.708*	0.456
	(0.336)	(0.255)	(0.344)	(0.272)	(0.331)	(0.265)
wsalesgr	-0.526	-0.566	-0.555	-0.562	-0.550	-0.564
	(0.434)	(0.476)	(0.439)	(0.477)	(0.439)	(0.476)
wbm	-0.207	0.038	-0.149	0.042	-0.146	0.039
	(0.308)	(0.316)	(0.306)	(0.314)	(0.301)	(0.315)
wmomt11	0.190	0.071	0.166	0.070	0.167	0.070
	(0.278)	(0.244)	(0.275)	(0.244)	(0.273)	(0.244)
log(marketcap)	0.118**	0.144**	0.122**	0.145**	0.124**	0.145**
	(0.051)	(0.060)	(0.050)	(0.060)	(0.050)	(0.060)
Observations	88,522	88,522	88,522	88,522	88,522	88,522
R^2	0.26914	0.27042	0.26939	0.27042	0.26938	0.27042
Within R^2	0.00247	0.00114	0.00281	0.00116	0.00280	0.00115
Industry		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes

to Kölbel et al. (2021b) which could be expected as we look at two different markets. Further, as we find no significant results after controlling for industry fixed effects, we do not see any reason to rerun the regression without the salient or material industries. The reason for such an exclusion is to further investigate if potential risk premiums are mainly driven by a handful of industries. In our case, excluding these industries to potentially find a risk premium can be seen as "p-hacking".

5.2.2 Disclosure quantity risk premium

We now turn to the quantity of risk disclosure and summarize the result of the cross-sectional return regression in Table 7. When controlling for industry effects, the quantity of disclosed physical climate change risk has a significant positive effect on stock returns, which is statistically significant at 5%. This effect is also economically significant because a one-standard-deviation increase in the quantity of physical risk disclosure leads to a monthly 13-bps increase in stock returns, or 1.6% annualized. No significant risk premium is observed for the quantity of transitional or total risk disclosure.

Our findings indicate that the quantity of physical climate change risk disclosure, in item 1A, is of importance to investors. We find that investors demand a risk premium because their risk perception increases relative to the quantity of disclosure, supporting the divergence argument of our hypothesis. These findings could be driven by the asymmetric distribution depicted in Figure 4, we therefore follow Bolton and Kacperczyk (2021) and rerun the regressions excluding salient industries.

The results for this exclusion are reported in Table 8 where we observe that the significant risk premium still persists when controlling for industry fixed effects. Under these conditions, the results are still economically significant given that a one-standard-deviation increase in the quantity of physical risk disclosure leads to a 10.9-bps monthly return or 1.31% annualized. Surprisingly, in Table 8 the quantity of physical climate change risk disclosure becomes weakly significant when industry fixed effects are not present.

We find that our results are not driven by these salient industries, indicating a robustness of our results. However, the economic significance decreased by 20%, indicating a lower sensitivity by investors in the remaining industries. In 4 we show that the sectors "Extractives & Minerals Processing" as well as "Infrastructure" disclose the highest quantity of physical climate change risk. As the salient industries are present in these sectors, the remaining sample will be more homogeneous, explaining the observed congruence in the physical risk premiums of models (1) and (2). Further, this indicates that the physical risk premiums in Table 7 and Table 8 are not necessarily due to a miss classification of industry.

Table 7:
Disclosure quantity and stock returns.
Sample period 2010 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

	monthly_return					
	(1)	(2)	(3)	(4)	(5)	(6)
wsentphys	0.011	0.044**				
	(0.014)	(0.016)				
wsenttrans			-0.012	0.008		
			(0.008)	(0.011)		
wsenttot					-0.007	0.010
					(0.006)	(0.008)
marketbeta	0.689*	0.626*	0.676*	0.631*	0.674*	0.624*
	(0.336)	(0.318)	(0.336)	(0.318)	(0.337)	(0.319)
wgross_profit	0.993**	0.475*	0.799**	0.498*	0.857**	0.514*
	(0.347)	(0.259)	(0.351)	(0.263)	(0.350)	(0.262)
wsalesgr	-0.536	-0.594	-0.526	-0.580	-0.523	-0.593
	(0.432)	(0.481)	(0.433)	(0.484)	(0.433)	(0.486)
wbm	-0.265	0.036	-0.200	0.036	-0.215	0.035
	(0.320)	(0.316)	(0.316)	(0.315)	(0.317)	(0.315)
wmomt11	0.197	0.059	0.191	0.069	0.196	0.065
	(0.286)	(0.245)	(0.280)	(0.245)	(0.282)	(0.246)
log(marketcap)	0.109*	0.148**	0.110*	0.147**	0.110*	0.148**
	(0.050)	(0.061)	(0.050)	(0.062)	(0.050)	(0.062)
Observations	88,522	88,522	88,522	88,522	88,522	88,522
R^2	0.26904	0.27055	0.26914	0.27044	0.26908	0.27047
Within R^2	0.00235	0.00132	0.00247	0.00117	0.00240	0.00123
Industry		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes

Table 8:
Disclosure quantity and stock returns: excluding salient industries.
Sample period 2010 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

	monthly_return					
	(1)	(2)	(3)	(4)	(5)	(6)
wsentphys	0.028*	0.044**				
	(0.014)	(0.016)				
wsenttrans			-0.007	0.004		
			(0.011)	(0.008)		
wsenttot					-0.0006	0.009
					(0.009)	(0.007)
marketbeta	0.756**	0.643*	0.756**	0.653*	0.751**	0.646*
	(0.328)	(0.314)	(0.322)	(0.312)	(0.325)	(0.313)
wgross_profit	0.903**	0.608**	0.822**	0.619**	0.869**	0.637**
	(0.353)	(0.260)	(0.340)	(0.258)	(0.342)	(0.260)
wsalesgr	-0.575	-0.576	-0.542	-0.551	-0.547	-0.566
	(0.440)	(0.474)	(0.442)	(0.477)	(0.441)	(0.476)
wbm	-0.111	0.116	-0.083	0.122	-0.092	0.116
	(0.341)	(0.359)	(0.339)	(0.356)	(0.340)	(0.357)
wmomt11	0.182	0.087	0.186	0.098	0.188	0.095
	(0.275)	(0.242)	(0.273)	(0.244)	(0.274)	(0.244)
log(marketcap)	0.124**	0.135**	0.122**	0.135**	0.124**	0.136**
	(0.049)	(0.055)	(0.052)	(0.055)	(0.051)	(0.055)
Observations	78,058	78,058	78,058	78,058	78,058	78,058
R^2	0.27286	0.27394	0.27282	0.27383	0.27280	0.27386
Within R^2	0.00229	0.00134	0.00224	0.00119	0.00221	0.00123
Industry		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes

To further investigate if our results are robust, we base the exclusion criteria on industry materiality of climate change risk rather than salient industries. For the materiality assessment we follow the Kölbel et al. (2021b) adjusted version of the procedure by Matsumura et al. (2018). This procedure requires four out of seven issues to be present in the Materiality Map® for climate risk to be considered a material risk towards the industry. After applying the exclusion criteria we rerun the regressions and report the results in Table 9. Again, the results show that the quantity of physical risk disclosure has a significant positive effect on returns. The physical risk premium is both greater and more statistically significant with and without industry fixed effects. Additionally, we find that the non-industry risk premium is economically significant: a one-standard-deviation increase in the quantity of physical risk sentences leads to a 9.93 bps monthly return or 1.19% annually. While the industry adjusted economic significance is 16.82 bps monthly return or 2.02% annually. Without the material industries present, we also find a significant risk premium related to total risk when adjusting for industry fixed effects. For economic significance a one-standard-deviation increase in the quantity of total climate change risk leads to a 14.2 bps monthly return or 1.7% annually.

We find both statistical and economical significant effects with and without the exclusions of salient and material industries, suggesting that there exists a consistent return premium related to the quantity of physical climate change risk disclosure. Outside of the material industries we also observe a statistically and economically significant effect from the quantity of total risk disclosure on returns. Our findings indicate that investors care about the disclosures of physical climate change risk and that they act upon these risks by requiring a premium.

Table 9:
Disclosure quantity and stock returns: excluding material industries.
Sample period 2010 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

	monthly_return					
	(1)	(2)	(3)	(4)	(5)	(6)
wsentphys	0.036***	0.061***				
	(0.010)	(0.015)				
wsenttrans			-0.004	0.015		
			(0.011)	(0.012)		
wsenttot					0.002	0.019**
					(0.007)	(0.008)
marketbeta	0.795**	0.670*	0.778**	0.678*	0.783**	0.670*
	(0.322)	(0.326)	(0.323)	(0.328)	(0.324)	(0.328)
wgross_profit	0.840**	0.560*	0.758**	0.609**	0.814**	0.624**
	(0.341)	(0.263)	(0.330)	(0.269)	(0.330)	(0.267)
wsalesgr	-0.295	-0.232	-0.262	-0.217	-0.269	-0.235
	(0.312)	(0.347)	(0.317)	(0.352)	(0.316)	(0.349)
wbm	-0.286	-0.030	-0.258	-0.013	-0.261	-0.022
	(0.281)	(0.276)	(0.280)	(0.272)	(0.277)	(0.274)
wmomt11	0.092	0.024	0.103	0.043	0.103	0.035
	(0.330)	(0.303)	(0.327)	(0.307)	(0.330)	(0.306)
log(marketcap)	0.116*	0.119*	0.115*	0.121*	0.117*	0.122*
	(0.055)	(0.059)	(0.055)	(0.059)	(0.055)	(0.059)
Observations	70,216	70,216	70,216	70,216	70,216	70,216
R^2	0.27045	0.27134	0.27036	0.27118	0.27036	0.27126
Within R^2	0.00237	0.00136	0.00225	0.00114	0.00224	0.00125
Industry		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes

5.3 Physical risk premium and riks factors

Because of our findings regarding a physical risk premium related to the quantity of risk sentences, we now assess whether the physical risk premium is related to well-known risk factors. We focus on two physical risk premiums; 1) full sample with industry fixed effects, 2) full sample excluded material industries and without industry fixed effects.

Table 10:
Time series regressions.
Sample period 2010 to 2020. Dependent variables are the risk premiums with the materiality adjustement and the industry fixed effects.

	matphys		indphys	
	(1)	(2)	(3)	(4)
(Intercept)	0.034***	0.031***	0.034***	0.033***
	(0.009)	(0.010)	(0.012)	(0.010)
Mkt.RF		-0.419		-0.239
		(0.449)		(0.288)
SMB		1.53**		0.527
		(0.659)		(0.495)
HML		-0.449		-0.453
		(0.614)		(0.612)
RMW		2.83***		0.237
		(0.813)		(0.527)
CMA		-0.267		-1.35*
		(0.990)		(0.704)
MOM		0.850***		0.048
		(0.319)		(0.397)
LIQ		-0.131		0.009
		(0.365)		(0.349)
Observations	132	132	132	132
R^2		0.12932		0.06972
Adjusted R^2		0.08017		0.01721

The regression results are shown in Table 10. In column one and three the mean of the physical risk premium is reported. In column two and four we show the regression results with the known riskfactors: Mkt.RF, SMB, HML, MOM, RMW, CMA, and LIQ. The results show how much of the physical risk premium, related to the amount of climate change risk sentences, is explained by the known risk factors. We use Newey-West standard errors with 12 lags to correct for autocorrelation. We find that the physical risk premium is only to a limited extent explained by the known risk factors. For both risk premiums the intercept is significant meaning that there is a statistically significant portion that is not explained by the known risk factors. This suggests that the physical risk premium persists even when these factor exposures are controlled for. We plot the timeseries of the cumulative return premiums in Figure 5 and Figure 5.

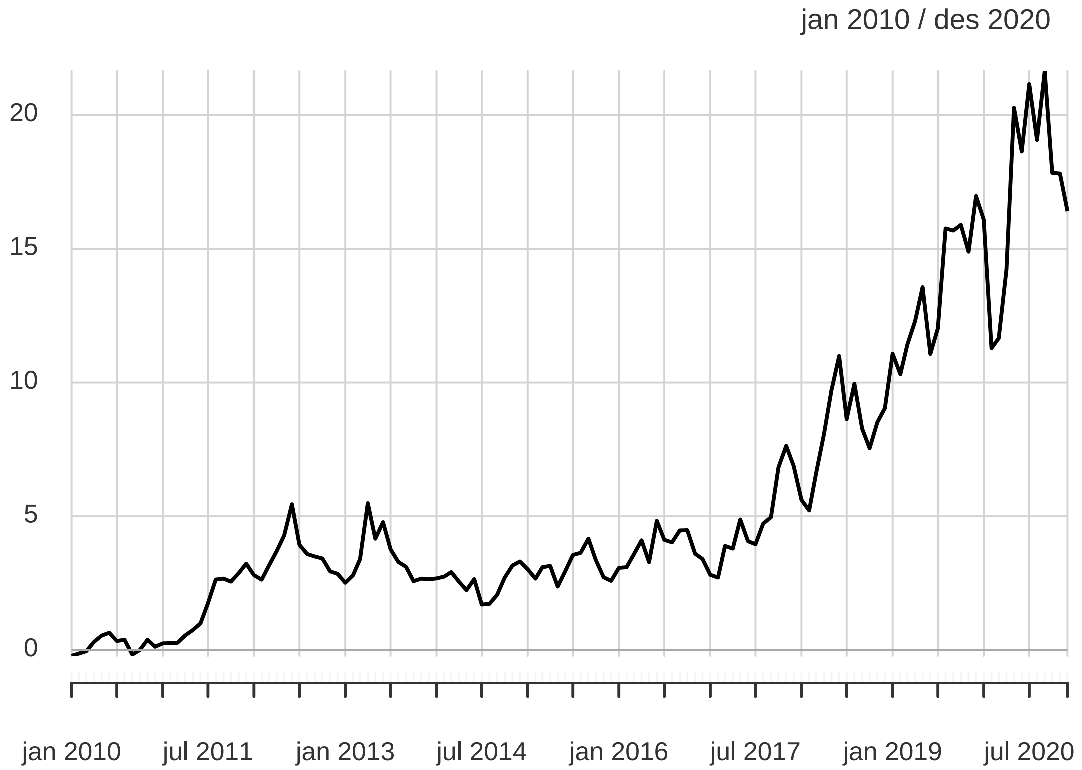

Figure 5: Physical disclosure cumulative return premium.
Non-material industries sample.

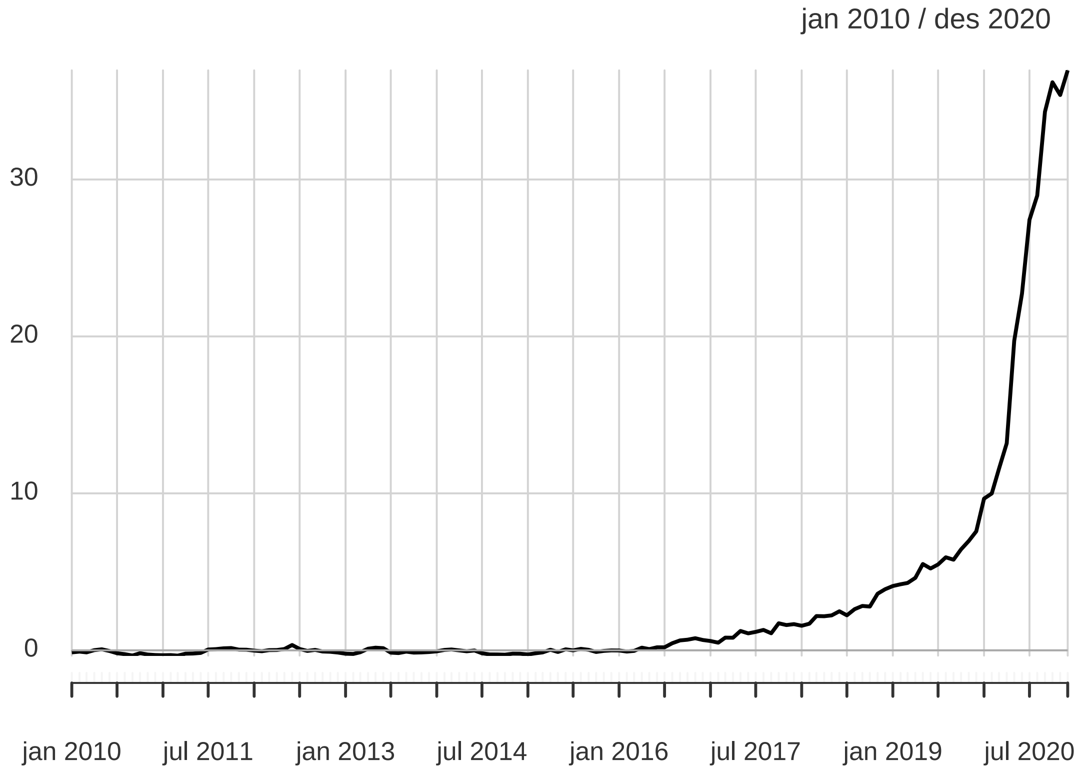

Figure 6: Physical disclosure cumulative return premium.
Full sample premium with industry fixed effects.

5.4 Paris Agreement implications

The Paris Agreement had a significant impact on the financial market, as shown by multiple papers, for example: Antoniuk and Leirvik (2021) finds that the Paris Agreement significantly impacted stock returns; Ilhan et al. (2020) find that the downside protection with options became more expensive for fossil fuel firms after the Paris Agreement; Kölbel et al. (2021b) finds that CDS spreads increased for transition risk disclosing firms after the Paris Agreement. In this section we aim to assess whether the Paris Agreement impacted investors' awareness regarding the disclosures of climate change risks. We hypothesize that the Paris Agreement increased the investors' awareness regarding the implications of climate change. To test this hypothesis we split our sample into the time-periods before and after the Paris Agreement, and then rerun the regression model (12) on each period. We set the pre period to include all observations from 2010 to 2015 and the post period to include 2016 till 2020.

5.4.1 Rate of disclosure

In Table 11 we present the results for the cross-sectional regressions on the two sub-periods. The results show that there exists a negative risk premium, weakly significant at 10%, for the disclosure rate of transition risk pre Paris Agreement. In the same period, the disclosure rate of total climate change risk is also related to a negative risk premium with significance at 5% and 10% with and without industry fixed effects. For the post Paris Agreement period, we find no significant effect regarding transitional or total risk. Additionally, we find that the rate of physical risk disclosure has no effect on stock returns, regardless of period.

For the pre Paris Agreement period, our results suggest that a higher rate of transitional or total risk disclosure reduces investors uncertainty. The uncertainty is reduced because the disclosure gives investors a clearer picture of the actual risks that the firms are facing, meaning that they can use a lower discount rate when valuing future cash flows, as argued by Damodaran (2020). As this effect is not observable in the post Paris Agreement period, it is an indication that the investor attention has changed over the span of these periods. However, as pointed out earlier and shown in Figure 2, these results can be driven by specific sectors with disproportionately high rates of disclosures. We therefore investigate if these industries impact our results through the previously explained procedure using the exclusion criterias for sectors and industries.

Table 11:

Disclosure rate and stock returns: Paris Agreement implications.

Sample period 2010 to 2020, pre paris is 2010 to 2015, post paris is 2016 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

Period	Pre Paris Agreement						Post Paris Agreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
wriskphys	-3.39	-0.693					-3.09	0.778				
	(2.26)	(1.72)					(4.28)	(1.44)				
wrisktrans			-2.86*	-1.57*					-1.38	0.139		
			(1.15)	(0.669)					(1.30)	(1.44)		
wrisktot					-2.28*	-1.17**					-1.20	0.309
					(0.898)	(0.362)					(1.22)	(1.02)
marketbeta	0.237	0.377	0.279	0.398	0.254	0.389	0.995	0.835	1.02*	0.833	1.01*	0.832
	(0.506)	(0.500)	(0.494)	(0.499)	(0.500)	(0.500)	(0.473)	(0.497)	(0.460)	(0.497)	(0.463)	(0.496)
wgross_profit	0.733**	0.209**	0.354	0.134***	0.415	0.170***	1.06	0.792	0.922	0.804	0.933	0.805
	(0.238)	(0.060)	(0.255)	(0.024)	(0.235)	(0.039)	(0.717)	(0.565)	(0.716)	(0.589)	(0.696)	(0.576)
wsalesgr	-0.289	-0.393	-0.293	-0.383	-0.292	-0.388	-0.823	-0.813	-0.863	-0.812	-0.858	-0.814
	(0.474)	(0.541)	(0.493)	(0.539)	(0.494)	(0.539)	(0.791)	(0.813)	(0.774)	(0.821)	(0.778)	(0.821)
wbm	-0.177	0.050	-0.117	0.058	-0.116	0.050	-0.191	0.179	-0.151	0.178	-0.145	0.177
	(0.111)	(0.154)	(0.085)	(0.152)	(0.086)	(0.153)	(0.630)	(0.558)	(0.612)	(0.550)	(0.601)	(0.552)
wmomt11	0.245	0.054	0.200	0.049	0.204	0.048	0.172	-0.144	0.165	-0.143	0.164	-0.143
	(0.411)	(0.388)	(0.393)	(0.387)	(0.393)	(0.388)	(0.342)	(0.290)	(0.345)	(0.290)	(0.342)	(0.291)
log(marketcap)	0.045	0.055	0.057	0.055	0.059	0.056	0.196*	0.253*	0.194*	0.254*	0.196*	0.254*
	(0.028)	(0.058)	(0.036)	(0.060)	(0.034)	(0.060)	(0.091)	(0.093)	(0.089)	(0.092)	(0.090)	(0.092)
Observations	43,406	43,406	43,406	43,406	43,406	43,406	45,116	45,116	45,116	45,116	45,116	45,116
R^2	0.24302	0.24517	0.24367	0.24525	0.24361	0.24523	0.28688	0.28946	0.28692	0.28946	0.28693	0.28946
Within R^2	0.00119	0.00044	0.00205	0.00054	0.00196	0.00052	0.00412	0.00190	0.00418	0.00190	0.00419	0.00190
Industry		Yes		Yes		Yes		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

We exclude the salient industries from both sub-samples and report the results in Table 12. Compared to the pre Paris Agreement results in Table 11 the effect that the rate of disclosure has on returns, decreases for both transitional risk and total risk when industry fixed effects are present. Under these conditions, the effect from transition risk is no longer significant, and total risk is only weakly significant. The exclusion of salient industries did not lead to any significant effects from the rate of physical risk disclosure on stock returns.

The results in Table 12 imply that the observed risk premium related to the rate of transition risk disclosure, from Table 11, was mainly driven by the firms within the salient industries. This means that inside the salient industries, investors are more sensitive towards the disclosure rate of transition risk. This finding is somewhat consistent with the findings of Bolton and Kacperczyk (2021), who find that investors' sensitivity towards carbon emissions appear to be different for firms within the salient industries than for firms in other industries.

Next, we assess whether exclusion based on material industries yields different results. We present these results in Table 13. We find that this exclusion shows none of the significant findings previously reported for the pre Paris Agreement period. Our results imply, that outside of material industries, the effect the rate of climate change risk disclosure has on returns is not significantly impacted by the Paris Agreement. This is in contrast with the findings of Kölbel et al. (2021b), but as we discussed earlier we were in general not able to find an effect by the rate of disclosure on returns.

Table 12:
Disclosure rate and stock returns: Paris Agreement implications, when excluding salient industries.
Sample period 2010 to 2020, pre paris is 2010 to 2015, post paris is 2016 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

Period	Pre Paris Agreement						Post Paris Agreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
wriskphys	-2.17	-0.938					-1.30	1.53				
	(2.43)	(1.88)					(3.36)	(1.28)				
wrisktrans			-3.13**	-1.37					0.556	0.810		
			(1.12)	(0.905)					(1.35)	(1.22)		
wrisktot					-2.33**	-1.03*					0.198	0.821
					(0.867)	(0.467)					(1.16)	(0.823)
marketbeta	0.265	0.406	0.321	0.422	0.296	0.416	1.16*	0.857	1.17*	0.850	1.17*	0.852
	(0.457)	(0.499)	(0.441)	(0.494)	(0.449)	(0.497)	(0.459)	(0.435)	(0.444)	(0.438)	(0.450)	(0.436)
wgross_profit	0.729*	0.408**	0.480	0.335**	0.549*	0.366**	0.931	0.862	0.963	0.902	0.941	0.891
	(0.303)	(0.133)	(0.283)	(0.102)	(0.270)	(0.096)	(0.724)	(0.560)	(0.695)	(0.591)	(0.691)	(0.576)
wsalesgr	-0.438	-0.568	-0.412	-0.549	-0.415	-0.555	-0.726	-0.552	-0.725	-0.543	-0.733	-0.546
	(0.520)	(0.597)	(0.553)	(0.602)	(0.551)	(0.599)	(0.834)	(0.801)	(0.805)	(0.792)	(0.811)	(0.795)
wbm	0.001	0.236	-0.010	0.236	-0.001	0.234	-0.072	0.165	-0.091	0.160	-0.086	0.160
	(0.147)	(0.185)	(0.131)	(0.186)	(0.132)	(0.185)	(0.703)	(0.667)	(0.704)	(0.659)	(0.698)	(0.660)
wmomt11	0.131	-0.071	0.094	-0.073	0.100	-0.073	0.266	0.017	0.269	0.019	0.269	0.018
	(0.411)	(0.394)	(0.401)	(0.393)	(0.401)	(0.394)	(0.322)	(0.311)	(0.325)	(0.312)	(0.324)	(0.312)
log(marketcap)	0.073	0.069	0.068	0.067	0.073	0.068	0.185	0.215*	0.185	0.218*	0.183	0.217*
	(0.039)	(0.056)	(0.043)	(0.058)	(0.042)	(0.058)	(0.090)	(0.093)	(0.093)	(0.092)	(0.092)	(0.092)
Observations	38,098	38,098	38,098	38,098	38,098	38,098	39,960	39,960	39,960	39,960	39,960	39,960
R^2	0.24985	0.25202	0.25030	0.25206	0.25022	0.25205	0.28905	0.29121	0.28905	0.29121	0.28904	0.29122
Within R^2	0.00082	0.00062	0.00141	0.00067	0.00132	0.00066	0.00415	0.00172	0.00415	0.00172	0.00414	0.00173
Industry		Yes		Yes		Yes		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 13:
Disclosure rate and stock returns: Paris Agreement implications, when excluding material industries.
Sample period 2010 to 2020, pre paris is 2010 to 2015, post paris is 2016 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

Period	Pre Paris Agreement						Post Paris Agreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
wriskphys	-0.125	1.01					-1.96	1.80				
	(2.25)	(1.79)					(3.50)	(2.15)				
wrisktrans			-1.58	-0.351					-1.42	0.717		
			(1.75)	(1.40)					(2.08)	(1.66)		
wrisktot					-0.952	0.131					-1.08	0.992
					(1.25)	(0.572)					(1.65)	(0.851)
marketbeta	0.388	0.428	0.389	0.429	0.381	0.425	1.10*	0.890	1.10**	0.885	1.10*	0.886
	(0.493)	(0.527)	(0.490)	(0.523)	(0.494)	(0.527)	(0.405)	(0.435)	(0.397)	(0.438)	(0.401)	(0.435)
wgross_profit	0.589*	0.249	0.465*	0.248	0.516*	0.263	0.929	0.903	0.838	0.942	0.862	0.933
	(0.259)	(0.185)	(0.228)	(0.185)	(0.220)	(0.166)	(0.721)	(0.610)	(0.694)	(0.637)	(0.683)	(0.609)
wsalesgr	-0.293	-0.382	-0.284	-0.382	-0.286	-0.385	-0.232	0.053	-0.256	0.057	-0.247	0.056
	(0.396)	(0.424)	(0.411)	(0.427)	(0.408)	(0.424)	(0.514)	(0.497)	(0.498)	(0.494)	(0.506)	(0.496)
wbm	-0.111	0.085	-0.121	0.085	-0.112	0.086	-0.317	0.057	-0.328	0.060	-0.321	0.060
	(0.140)	(0.183)	(0.139)	(0.182)	(0.138)	(0.181)	(0.571)	(0.486)	(0.593)	(0.485)	(0.581)	(0.484)
wmomt11	0.197	0.047	0.188	0.046	0.192	0.047	0.044	-0.135	0.038	-0.133	0.038	-0.134
	(0.448)	(0.441)	(0.439)	(0.440)	(0.441)	(0.440)	(0.451)	(0.418)	(0.444)	(0.419)	(0.445)	(0.419)
log(marketcap)	0.053	0.041	0.050	0.042	0.053	0.042	0.190	0.211*	0.184	0.214*	0.186	0.213*
	(0.042)	(0.074)	(0.045)	(0.070)	(0.045)	(0.071)	(0.101)	(0.093)	(0.096)	(0.091)	(0.097)	(0.092)
Observations	34,167	34,167	34,167	34,167	34,167	34,167	36,049	36,049	36,049	36,049	36,049	36,049
R^2	0.24285	0.24450	0.24295	0.24450	0.24292	0.24450	0.28929	0.29078	0.28931	0.29077	0.28931	0.29079
Within R^2	0.00090	0.00053	0.00104	0.00052	0.00099	0.00052	0.00389	0.00171	0.00392	0.00170	0.00392	0.00171
Industry		Yes		Yes		Yes		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

5.4.2 Quantity of disclosure

In this final section of the Paris Agreement implication assessment, we look at the quantity of disclosure and its effect on the cross-section of returns for the periods before and after the Paris Agreement. The results are reported in Table 14 and show a significant risk premium, related to the quantity of physical climate change risk disclosure, post Paris Agreement. On the other hand, we find no evidence for such a premium, pre Paris Agreement. For the quantity of transition risk and total risk disclosure, we find no significant risk premium, regardless of period.

The results in Table 14 suggest that the Paris Agreement had an impact on investor awareness regarding physical climate change risk. We argue this because the risk premium is only significant in the post Paris Agreement period, indicating an increase of investors' risk perception. To purely attribute this to the Paris Agreement is not possible due to other events which may have had a significant impact as well, such as the Trump election or the Covid pandemic. Regardless, our findings indicate significant differences pre and post the Paris Agreement, that are in line with the findings of previous studies.

Further, we continue with the same approach as before and rerun the regression with salient industries excluded. The results are reported in Table 15, and show that removing salient industries increases the physical risk premium for the post Paris Agreement period when industry fixed effects are not included. With industry fixed effects we are not observing any notable change. Additionally, we find that the risk premium related to the quantity of total climate change risk disclosure is positive and weakly significant at 10%. We also notice a significant negative risk premium related to the transition and total risk in the pre Paris Agreement period, when not controlling for industry fixed effects.

These results indicate that the observed impact from the Paris Agreement on the risk premium related to the quantity of physical risk disclosure, was not driven by the salient industries but is persistent across a wide variety of industries. The observed negative risk premiums pre Paris Agreement are due to not including industry fixed effects, meaning that industry specific variation has been attributed to the quantity of disclosure. We do the final assessment, running the regression on the sample with material industries excluded for both time-periods.

Our results in Table 16 show that the risk premiums for physical climate change disclosure still persist and have increased when the material industries are removed. We also observe that total climate change risk disclosure is positive and significant at 5% post Paris Agreement when controlling for industry effects and excluding material industries. At 10% significance, the physical risk premium is also observable in the pre Paris Agreement period for this adjusted sample.

The increased physical risk premium post Paris Agreement, indicates that investors are more sensitive towards the quantity of physical risk disclosure for firms in industries where climate change is considered a non-material issue. Under these conditions, both the physical and total risk premium is substantially larger for the period after the Paris Agreement than before, indicating a change in investors' awareness.

Table 14:
Disclosure quantity and stock returns: Paris Agreement implications.
Sample period 2010 to 2020, pre paris is 2010 to 2015, post paris is 2016 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

Period	Pre Paris Agreement						Post Paris Agreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
wsentphys	-0.018	0.006					0.036**	0.082**				
	(0.021)	(0.009)					(0.012)	(0.022)				
wsenttrans			-0.026	-0.009					0.001	0.024		
			(0.013)	(0.014)					(0.007)	(0.015)		
wsenttot					-0.018	-0.005					0.004	0.026
					(0.009)	(0.009)					(0.005)	(0.012)
marketbeta	0.256	0.378	0.266	0.393	0.255	0.388	1.05*	0.789	1.03*	0.805	1.04*	0.789
	(0.502)	(0.502)	(0.498)	(0.499)	(0.501)	(0.501)	(0.453)	(0.499)	(0.458)	(0.497)	(0.457)	(0.497)
wgross_profit	0.722**	0.200**	0.409	0.155***	0.466	0.174***	1.19	0.831	1.11	0.906	1.17	0.927
	(0.227)	(0.061)	(0.244)	(0.038)	(0.235)	(0.041)	(0.744)	(0.563)	(0.733)	(0.568)	(0.731)	(0.565)
wsalesgr	-0.281	-0.395	-0.252	-0.371	-0.251	-0.378	-0.850	-0.876	-0.824	-0.847	-0.822	-0.870
	(0.469)	(0.541)	(0.476)	(0.536)	(0.476)	(0.537)	(0.794)	(0.833)	(0.779)	(0.841)	(0.783)	(0.848)
wbm	-0.199	0.050	-0.136	0.050	-0.134	0.051	-0.274	0.171	-0.237	0.171	-0.260	0.172
	(0.114)	(0.154)	(0.092)	(0.155)	(0.095)	(0.155)	(0.653)	(0.558)	(0.643)	(0.555)	(0.643)	(0.556)
wmomt11	0.254	0.055	0.224	0.055	0.232	0.055	0.169	-0.188	0.181	-0.155	0.180	-0.172
	(0.417)	(0.387)	(0.396)	(0.385)	(0.401)	(0.386)	(0.354)	(0.297)	(0.351)	(0.298)	(0.351)	(0.302)
log(marketcap)	0.035	0.054	0.042	0.052	0.041	0.052	0.190*	0.263**	0.190*	0.262*	0.191*	0.266*
	(0.032)	(0.060)	(0.034)	(0.058)	(0.033)	(0.058)	(0.086)	(0.094)	(0.087)	(0.096)	(0.087)	(0.096)
Observations	43,406	43,406	43,406	43,406	43,406	43,406	45,116	45,116	45,116	45,116	45,116	45,116
R^2	0.24291	0.24517	0.24345	0.24520	0.24332	0.24518	0.28692	0.28988	0.28681	0.28962	0.28683	0.28977
Within R^2	0.00105	0.00044	0.00175	0.00048	0.00158	0.00045	0.00417	0.00249	0.00402	0.00212	0.00405	0.00233
Industry		Yes		Yes		Yes		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 15:
Disclosure quantity and stock returns: Paris Agreement implications, when excluding salient industries.
Sample period 2010 to 2020, pre paris is 2010 to 2015, post paris is 2016 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

Period	Pre Paris Agreement						Post Paris Agreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
wsentphys	-0.001	0.005					0.051**	0.082**				
	(0.020)	(0.013)					(0.012)	(0.020)				
wsenttrans			-0.033**	-0.015					0.016	0.019		
			(0.010)	(0.012)					(0.015)	(0.011)		
wsenttot					-0.021**	-0.008					0.017	0.024*
					(0.006)	(0.006)					(0.011)	(0.009)
marketbeta	0.274	0.408	0.318	0.424	0.302	0.419	1.19*	0.812	1.17*	0.837	1.17*	0.820
	(0.452)	(0.498)	(0.446)	(0.495)	(0.450)	(0.497)	(0.446)	(0.439)	(0.442)	(0.432)	(0.444)	(0.432)
wgross_profit	0.722*	0.397**	0.495	0.345**	0.557*	0.371**	0.998	0.894	1.05	0.947	1.08	0.969
	(0.289)	(0.115)	(0.272)	(0.115)	(0.270)	(0.111)	(0.723)	(0.564)	(0.682)	(0.554)	(0.690)	(0.559)
wsalesgr	-0.444	-0.570	-0.375	-0.530	-0.380	-0.541	-0.796	-0.612	-0.722	-0.550	-0.742	-0.571
	(0.516)	(0.596)	(0.549)	(0.609)	(0.544)	(0.603)	(0.819)	(0.792)	(0.822)	(0.802)	(0.820)	(0.801)
wbm	-0.010	0.236	0.015	0.247	0.024	0.246	-0.112	0.150	-0.115	0.149	-0.127	0.142
	(0.148)	(0.186)	(0.126)	(0.185)	(0.130)	(0.184)	(0.725)	(0.675)	(0.720)	(0.665)	(0.723)	(0.668)
wmomt11	0.135	-0.070	0.101	-0.072	0.113	-0.071	0.248	-0.024	0.262	0.012	0.253	-0.004
	(0.414)	(0.394)	(0.402)	(0.392)	(0.406)	(0.394)	(0.328)	(0.317)	(0.328)	(0.317)	(0.329)	(0.320)
log(marketcap)	0.068	0.068	0.063	0.066	0.066	0.067	0.185	0.222*	0.192	0.223*	0.194	0.226*
	(0.042)	(0.058)	(0.043)	(0.058)	(0.042)	(0.058)	(0.090)	(0.092)	(0.097)	(0.094)	(0.096)	(0.094)
Observations	38,098	38,098	38,098	38,098	38,098	38,098	39,960	39,960	39,960	39,960	39,960	39,960
R^2	0.24981	0.25202	0.25027	0.25207	0.25011	0.25204	0.28922	0.29157	0.28913	0.29128	0.28921	0.29141
Within R^2	0.00076	0.00062	0.00138	0.00069	0.00117	0.00065	0.00439	0.00223	0.00426	0.00182	0.00437	0.00200
Industry		Yes		Yes		Yes		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 16:
Disclosure quantity and stock returns: Paris Agreement implications, when excluding material industries.
Sample period 2010 to 2020, pre paris is 2010 to 2015, post paris is 2016 to 2020. Dependent variable is monthly_return. Regression includes year-month and industry fixed effects with standard errors clustered at the firm and year level. Industry classification by SICS sub-sector. ***1% significance; **5% significance; *10% significance.

Period	Pre Paris Agreement						Post Paris Agreement					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
wsentphys	0.025	0.034*					0.046***	0.092**				
	(0.019)	(0.014)					(0.008)	(0.022)				
wsenttrans			-0.009	0.003					0.002	0.027		
			(0.019)	(0.017)					(0.013)	(0.015)		
wsenttot					-0.003	0.007					0.008	0.032**
					(0.013)	(0.009)					(0.007)	(0.011)
marketbeta	0.395	0.421	0.389	0.424	0.388	0.419	1.15**	0.840	1.12**	0.866	1.14**	0.845
	(0.488)	(0.527)	(0.489)	(0.527)	(0.490)	(0.528)	(0.396)	(0.435)	(0.399)	(0.438)	(0.398)	(0.438)
wgross_profit	0.618*	0.265	0.509*	0.272	0.561*	0.289	0.993	0.922	0.944	1.01	1.00	1.03
	(0.244)	(0.171)	(0.239)	(0.174)	(0.234)	(0.171)	(0.717)	(0.605)	(0.693)	(0.616)	(0.694)	(0.610)
wsalesgr	-0.308	-0.400	-0.276	-0.391	-0.286	-0.404	-0.296	-0.007	-0.244	0.051	-0.250	0.030
	(0.394)	(0.418)	(0.402)	(0.419)	(0.401)	(0.415)	(0.498)	(0.490)	(0.500)	(0.501)	(0.505)	(0.500)
wbm	-0.132	0.071	-0.115	0.083	-0.110	0.076	-0.362	0.029	-0.333	0.055	-0.341	0.046
	(0.143)	(0.182)	(0.139)	(0.182)	(0.139)	(0.183)	(0.592)	(0.493)	(0.583)	(0.484)	(0.581)	(0.485)
wmomt11	0.190	0.042	0.195	0.047	0.197	0.046	0.030	-0.192	0.049	-0.145	0.047	-0.168
	(0.451)	(0.440)	(0.444)	(0.442)	(0.447)	(0.441)	(0.452)	(0.411)	(0.452)	(0.426)	(0.457)	(0.427)
log(marketcap)	0.052	0.043	0.050	0.043	0.052	0.044	0.189	0.217*	0.188	0.220*	0.191	0.222*
	(0.045)	(0.072)	(0.046)	(0.072)	(0.045)	(0.071)	(0.098)	(0.091)	(0.098)	(0.093)	(0.097)	(0.092)
Observations	34,167	34,167	34,167	34,167	34,167	34,167	36,049	36,049	36,049	36,049	36,049	36,049
R^2	0.24290	0.24456	0.24289	0.24450	0.24286	0.24452	0.28942	0.29123	0.28926	0.29091	0.28929	0.29110
Within R^2	0.00097	0.00061	0.00095	0.00052	0.00091	0.00054	0.00407	0.00233	0.00385	0.00189	0.00390	0.00215
Industry		Yes		Yes		Yes		Yes		Yes		Yes
Year/month	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

5.4.3 Discussion Paris Agreement

One interesting observation is that we are not able to detect any significant relationship between the quantity of disclosed transitional climate change risk and returns, for either period. This result is somewhat in contrast to our findings in Table 11, where we found the transitional climate change risk disclosure rate to have a weakly significant uncertainty reducing effect in the pre Paris Agreement period. If the quantity is not important, but the rate is, then what was really measured? On the one hand, one could argue that the rate of disclosure for transition risk is somewhat of a quality measure, a "signal to noise" measure or file-length normalized as by Kölbel et al. (2021b). On the other hand, Campbell et al. (2014) found that firms with higher risk, disclose more risk factors. Hypothetically, if a firm has a transitional disclosure rate of 1 it would mean that this firm only disclosed sentences that were related to transitional climate change, meaning that this firm only disclosed one risk factor. One could therefore argue that the higher the rate of transitional climate change risk disclosure the lower the total amount of disclosed risk factors. This could further mean that investors did not see the rate of disclosure of transition risk as important and therefore rather looked for all the other disclosures of risk. We shed light on this because of our observation that the uncertainty reducing effect was only weakly significant before adjusting for salient and material industries, where the rate of disclosure as shown in Figure 3 was disproportionately high compared to the full sample. For example, "Extractives & Minerals Processing" have an average disclosure rate of 30% leaving only 70% for other risk disclosures.

Alternatively, for transitional risk assessment the methods of measurement greatly exceed those for physical risk assessment (Kölbel et al., 2021b), which in turn explains the lack of investor attention to disclosures. One example is Firm-level carbon emissions which Bolton and Kacperczyk (2021) find to impact stock returns. We did not assess whether there exists correlation between carbon emissions and transitional risk disclosure but as shown in Figure 3 and Figure 4, such a correlation is highly likely.

For physical risk we are able to detect a statistically and economically significant risk premium only for the post Paris Agreement period. The economic significance shows that a one-standard-deviation increase in physical risk disclosure leads to a

10.28-bps increase in stock returns or 1.23% annually. The increase indicates that investors in the post Paris Agreement period were presented with new risk factors that they were not aware of previously. For example, risks related to an increasing frequency of extreme weather events.

6 Conclusion

Our evidence suggests that not all climate change risk disclosures affect US stock returns. We demonstrate this with a cross-sectional return analysis, using a metric for firm level climate change risk disclosure. The metric is based on the disclosures of risk in Item 1A in 10-k filings, classified by a BERT algorithm that Kölbel et al. (2021b) fine tuned to identify climate change topics. Our findings suggest that after the Paris Agreement a consistent risk premium exists for the disclosure of physical climate change risk. The premium is mostly related to the quantity of physical climate change disclosure and is both statistically and economically significant. We are not able to find consistent results for the quantity of disclosed total or transitional climate change risks. Notably, the rate of disclosure has no consistent effect on returns. We exclude salient industries and industries where climate change risk is of material matter, and demonstrate that the risk premium for total and transitional risk is driven mainly by these industries or sectors. On the contrary, the risk premium associated with the quantity of physical climate change risk disclosure is persistent outside of these industries. Additionally, we find that the Paris Agreement increased investor attention towards the disclosures of physical climate change risk. After the Paris Agreement, the quantity of disclosed physical climate change risk increases the risk perception of investors, confirming that investors care about the disclosures of physical climate change risk.

7 Further research

It could be interesting to look at the rate of specific risk disclosures and analyze if there exists an uncertainty reduction effect in general for firms that disclose disproportionately high rates of single industry specific risk factors. For example, we find that industries that disclose disproportionately high rates of climate change risk potentially have this effect.

8 References

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