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Author (last name, first name):	Fliegel, Philip
Student ID number:	11932893
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Examiner (degree, first name, last name):	Univ. Prof. Dr. Armon Rezai and Prof. Irene Monasterolo

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The Climate Transition Risk Exposure of Holding Companies and its Implication on Financial Market Pricing

Abstract. There is growing awareness of the macroeconomic and financial implications of climate change. In this regard, the 2015 Paris Agreement highlighted the responsibility of the financial sector to massively increase investments into sustainable low carbon firms while simultaneously divest from high carbon activities in order to facilitate the decarbonization of the economy and avoid stranded assets as well as shocks to financial stability (UNFCCC, 2016). This thesis contributes to research in Climate Finance by examining the exposure of global holding companies to climate transition risk and by analyzing its implication on financial markets. Therefore, firms' 4-digit NACE codes are reclassified into Climate Policy Relevant Sectors (CPRS), which take into consideration companies' greenhouse gas emissions, relevance for climate policy and role in the energy value chain (Battiston et al., 2017). The following part of the work compares the financial market pricing of firms with more/less risky business in terms of climate transition risk/CPRS exposure by means of a Capital Asset Pricing Model, a Fama French 3-Factor Model and rolling regressions. Results for the CPRS exposure of global holding companies indicate that the overall direct exposure to CPRS is significant but low, as only 7.5% of overall revenue is earned in these respective sectors. Results for the pricing of several dirty portfolios indicate that the market underestimates the climate transition risk exposure of firms albeit showing a clearly reversing trend. Most notably, the systematic risk (beta) of several dirty portfolios is priced in line or below the overall market portfolio over the whole length of the time series. Interestingly, results from rolling regressions show strongly rising beta values for the dirty- as well as the very dirty portfolio, particularly after the Paris Agreement. Therefore, one can say that financial markets start to price climate transition risk more heavily than before. These findings are relevant as they contribute to a better disclosure of climate related risks while also indicating that financial markets tentatively start to be more aware of political announcements to phase out fossil fuels.

Master Thesis by Philip Fliegel

Supervisors: Univ. Prof. Dr. Armon Rezai and Prof. Irene Monasterolo

Msc Socio-Ecological Economics and Policy

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List of Abbreviations

Abbreviation	Explanation
CAPM	Capital Asset Pricing Model
CPRS	Climate Policy Relevant Sectors
E	Expected Value
EU	European Union
GHG	Greenhous Gas
HML	High Minus Low
IPCC	Intergovernmental Panel on Climate Change
MC	Market Capitalization
MSCI	Morgan Stanley Capital International
N	Number
NACE	Nomenclature Statistique des Activités Économiques dans la Communauté Européenne
Obs	Observations
OLS	Ordinary Least Squares
R	Return
RF	Risk Free Rate of Return (Approximated by the 1 Month US Treasury Bill Rate)
RM	Return of the Market Portfolio
SMB	Small Minus Big
SP	Standard & Poor's
Std. Dev.	Standard Deviation
US	United States
V	Variance
$\boldsymbol{\alpha}$	Jensen's Alpha Coefficient
$\boldsymbol{\beta}$	Beta Coefficient
$\boldsymbol{\varepsilon}$	Serially Uncorrelated Random Error Term
$\boldsymbol{\sigma^2}$	Squared Standard Deviation
$\boldsymbol{\varphi}$	Equal Weighting Factor
$\boldsymbol{\omega}$	Value Weighting Factor

1. Introduction

In order to prevent catastrophic damages, the Paris Agreement of 2015 obliges participating states to limit anthropogenic global warming well below two degrees by radically transforming economies away from fossil fuel energy consumption (UNFCCC, 2016). According to the most recent report from the Intergovernmental Panel on Climate Change (IPCC), there is still time to avoid the worst consequences of global warming, however this window of opportunity is closing quickly as human societies increase emissions as opposed to radically cut greenhouse gas (GHG) emissions. Under a very low GHG emission scenario, IPCC projections indicate that global warming above two degrees Celsius would be extremely unlikely if humankind cut emission towards net neutrality by around 2050 (IPCC, 2021). Failing to achieve the two-degree target would cause catastrophic, but well-known consequences such as sea level rise, increasing likelihood of extreme weather events or biodiversity loss (Stern, 2015). Such *physical climate risk* would not only severely threaten millions of people and nature but also significantly impact immobile physical assets as well as productivity levels (Burke et al., 2015), thereby severely affecting global production and financial stability. The exact scope and timing of such climate impacts are impossible to project due to high levels of uncertainty (Monasterolo, 2020) connected to biophysical climate tipping points (e.g., Arctic sea-ice loss or weaker Atlantic circulation), which might induce further impacts in a catastrophic downward spiral (Lenton et al., 2019).

Additional to physical climate risk, the transition towards a low carbon economy might cause *climate transition risk.* However, both physical and transitionary risks are often intertwined, and transition risks might also be caused by rising awareness about physical risks (Battiston et al., 2020). Further drivers of climate transition risk include technological shocks to the costs of renewable energy, regulatory shocks to ambitious climate policy or changing expectations of market participants. All of these drivers can lead to an abrupt change in expectations about the future of high carbon assets, namely that a low carbon transition might occur sooner than previously expected (Monasterolo, 2020). In such a scenario, large parts of remaining fossil reserves as well as physical carbon infrastructure are at risk of devaluation and write offs causing fundamental climate transition risk for fossil fuel related companies (Van der Ploeg & Rezai, 2020b). An example of such changing expectation is provided by the newest flagship report from the International Energy Agency on the future of energy, which for the first time describe a detailed roadmap for the energy sector to reach the net zero emissions by 2050 (IEA, 2020). Climate transition risk mainly concerns high carbon industries such as the energy sector, however, given their central role in most contemporary economies, losses in the energy sector can be expected to also influence related industries along the value chain and eventually create cascading effects which systematically could affect the whole economy and ultimately threaten financial stability (Battiston et al., 2019). Such transitionary climate risks are mainly associated with the notion of a disorderly low carbon transition. While a climate transition can be *orderly*, i.e., enacted early on and fully anticipated by market participants; late, uncoordinated and unanticipated climate policy bears the risk of a *disorderly transition* towards a low carbon society. In a disorderly transition, investors cannot anticipate the transition, leading to potentially long-lasting negative impacts on both the economy as well as the financial sector. High carbon firms would also not have the time to adjust the business strategy away from fossil fuels, leading to abrupt changes in market share. In a worst-case disorderly transition, high carbon companies could not service their debt obligations anymore leading to losses throughout the economy (Monasterolo, 2020).

Climate risk has increasingly become important for financial institutions and investors (Carney, 2015). Several initiatives emerged which aim at a better disclosure of climate related risks as well as the initiation of regular climate stress tests. In 2017 some central banks joined forces and created the network for greening the financial system (NGFS), which explicitly recommended financial stability climate stress testing (NGFS, 2019) and also generated several climate scenarios to do so (NGFS, 2020). Another initiative emerged based on the Financial Stability Board, which installed a Task Force on Climate-related Financial Disclosures that aims at better disclosure of climate risk related risks on the company level (FSB, 2020). On the European Union (EU) level, the EU Commission created a high-level expert group on sustainable finance to set standards for the identification of sustainable investments. Thereby the EU seeks to scale up investments in low carbon industries while simultaneously divest from carbon intensive activities (European Commission, 2020). Estimates about the scope of the required investments vary considerably and are highly sensitive to assumptions about future cost of electricity, future electricity demand and emission reduction scenarios. Scholars modelled the investment costs required to achieve a low carbon transition in the European energy sector and found total numbers ranging from 127 billion Euros to 225 billion Euros under different electricity cost development scenarios (Alessi et al., 2019).

Given the growing awareness about physical and transitional risks associated with climate change one would expect traditional economic financial models to prominently feature these risks within the respective models. However, there are several reasons why this has not happened sufficiently and why traditional risk models, which assume perfect information and normal distributions (Black & Scholes, 1973), are ill equipped to grasp climate change induced risks, as a new class of risk, to their full extent (Battiston et al., 2021a). Climate risks differ from traditional financial risks due to several reasons. Most notably, future scenarios of an unprecedented event cannot be based on past experiences. Climate risks are *nonlinear* in their impact and traditional normally distributed risk assessments based on historic data, fall short in grasping the scope of the problem. Additionally, the real consequences of climate change are, as of today, unknown. Thus, the risks are situated in an environment of *deep uncertainty.* Financial markets are also well known for the *short-term focus* on profits, while climate risks are likely to impact humankind over the next centuries. Finally, *endogeneity* of climate risk perception by actors involved and *complexity* in understanding the complex adaptive systems further complicates grasping climate risks adequately (Ackerman, 2017; Battiston et al., 2019; Kriegler et al., 2013; Monasterolo, 2020).

Companies around the world face climate transition risk to different degrees. How exposed companies are to the risk of a disorderly low carbon transition mainly depends on the relative sector of operation and utilized technology (Battiston et al., 2020). While the standard classification for economic activities, the NACE Rev2 codes, classify economic sectors in the European community in a very detailed manner, they lack a detailed differentiation how companies are exposed to climate transition risk, given their field of operation and utilized technology. Therefore, Battiston et al. (2017) reclassified companies from 4-digit NACE codes into nine mutually exclusive climate policy relevant sectors (CPRS). The classification is based on three criteria. First, a firm's direct or indirect GHG emissions. Second, the relevance for climate policy, including the sensitivity to regulatory climate policy shifts. An example is the carbon leakage regulation of the EU. The last criteria is the role of the economic activity in the energy value chain. Thereby the CPRS methodology goes beyond solely focusing on GHG emissions and allows to categorize firm's climate risk exposure to a high degree of granularity.

More precisely, the main CPRS encompass Fossil Fuel, Utility, Energy Intensive, Buildings, Transportation, Agriculture, Finance, Scientific R&D and Other (Battiston et al., 2020). These main sectors can be further refined into granular CPRS by differentiating firms based on their energy technology (Bressan et al., 2021). However, CPRS do not only cover potential losses from climate transition, but also provide a classification for business activities, which might be affected positively by a climate transition, e.g., renewable energy producers (Battiston et al., 2020).

This thesis aims at using the CPRS methodology in order to differentiate global holding companies based on their relative exposure to climate transition risk. Since firms are usually engaged across different sectors, detailed revenue information is utilized to estimate the shares of company's activities in respective CPRS. This work focuses on global holding companies as no detailed CPRS exposure classification was ever conducted for this range of NACE codes. Furthermore, these companies usually fall under the radar because their NACE codes as financial holdings would classify them into CPRS 7 – Finance. However, holdings operate through subsidiaries, which might be engaged in very climate relevant industries such as fossil fuel extraction or aviation. Thus, special scrutiny in reclassifying NACE codes into CPRS is required. This thesis then aims at using the results of the detailed companies' CPRS exposure databank in order to analyze whether financial markets price climate transition risk of global holdings.

The findings contribute to the debate around Climate Finance in two ways: First, it furthers an evidence-based classification of companies into CPRS as opposed to an oversimplified dichotomy of "clean" or "dirty" firms. Firms are complex entities, which operate across several sectors, across many subsidiaries. Hence, only few firms are 100 % clean or dirty. The CPRS classification helps overcoming simplified thinking by understanding firms' operations in terms of their "dirtiness", i.e., their detailed exposure to climate transition risk across all fields of operation. This is particularly true for global holding companies, which pro forma do not carry too much climate transition risk but through subsidiaries might be directly climate policy relevant. The thesis thus fills the gap in the correct classification of holding companies into a wider company database, which builds on Battiston et al. 2017 and Battiston et al. 2020 and aims at reclassifying all NACE codes into CPRS. The thesis thereby facilitates better disclosure of climate transition risk, which is pivotal for investors who want to understand the detailed climate transition risk exposure of their portfolios.

Second, it helps understand if and to which degree financial markets are pricing firms' climate transition risks into today's security prices. Thereby financial market participants can better understand whether a reduction in high carbon investments might increase the value of investor portfolios. The results of this thesis can also help assess the credibility of policy makers promising a green energy transition. This is especially interesting for the Paris Agreement as it showed the global ambition to limit warming below two degrees Celsius. Furthermore, insights from the (mis)pricing of climate transition risk on financial markets can contribute to the debate about the efficiency of financial markets, especially in the long term.

2. Literature Review

The review of the relevant literature will start with highlighting the relevance of financial markets in a low carbon transition by introducing literature on forward looking climate financial risk models as well as stranded assets. It continues with literature on the utilization of the CPRS methodology and theoretical pricing models. In the next sections results from studies investigating the pricing of both physical and transitional climate risks on financial markets are highlighted. Finally, a gap in the literature is identified and two research questions are formulated with the aim of addressing this knowledge gap.

Traditional IPCC scenarios use large scale integrated assessment models, which utilize different climate policy scenarios and return socioeconomic output trajectories. However, these models fail to consider the pivotal role of financial markets, which itself shape climate mitigation pathways. The likelihood of a (dis)orderly transition is thus not exogenous to the financial market but depends on the perception and expectations of financial market participants. In other words: the financial market is influenced by climate policy and climate scenarios but endogenously also shapes the risk of a disorderly transition (Battiston et al., 2021b). In order to account for the two-way relation between the financial system and climate mitigation pathways, scholars proposed an integrated framework, which models different climate transition pathways using a combination of forward-looking integrated assessment models for socioeconomic- and GHG emissions scenarios and combined these results with climate financial risk models in order to include financial markets into future scenarios. Results show that financial markets play a pivotal role in stabilizing the climate transition. Whenever financial markets act as an enabler of ambitious climate policies an orderly transition (without stranded assets and price volatility) emerges, even when climate policy implementation occurs rather late, i.e., only after 2030. However, financial markets can also work against ambitious climate transitions, for example by neglecting climate risks or by delaying the reallocation of funds away from fossil fuels. The financial sector as a barrier can lead to a disorderly transition, even when the timing of climate policy is early and starts immediately. Model projections yield significantly higher asset volatility and stranded assets within a disorderly transition. As a result, the stability of the financial markets could be affected severely (Battiston et al., 2021b).

Within a disorderly low carbon transition there is considerable risk of asset stranding. There is no generally accepted definition on carbon stranded assets, but the term describes generally write-offs in high carbon assets. Such abrupt changes in the market value of fossil assets are a potential consequence of a disorderly low carbon transition, given two conditions: There is a sudden and unanticipated change in the profitability of high carbon assets and these assets must be locked into the fossil value chain, i.e., they cannot be made profitable elsewhere. There are four different types of asset stranding (Van der Ploeg & Rezai, 2020b). First, McGlade and Ekins (2015) estimate how much of the proven fossil fuel reserves will remain unburned if humankind is able to limit global warming below two degrees. The results amount to four fifths (one third) of global coal (oil) and show the huge scope of *stranded carbon* as the first type of stranded assets. Second, physical capital such as oil platforms or excavators will strand once the demand for fossil fuel softens. Third, prices will react sooner than the actual end of the carbon era, thus the valuation of assets at risk of stranding might decrease earlier than currently expected. Finally, policy announcements are not certain, but if uncertainty about their implementation is reduced in the future, carbon assets can suffer an immediate loss in market value (Van der Ploeg & Rezai, 2020a, 2020b).

2.1 The CPRS Methodology

The methodology of classifying companies into CPRS was first introduced by Battiston et al. (2017) and has since been utilized by leading financial institutions such as the Austrian National Bank (Battiston et al., 2020), the European Insurance and Occupational Pensions Authority (Battiston et al., 2019), the European Central Bank (European Central Bank, 2019) and the

European Banking Authority (EBA, 2020) in order to assess the climate transition risk exposure of their loans and securities, measured via the CPRS exposure. A good example for the classification of climate transition risk exposure of financial instruments to CPRS is provided by a financial impact assessment of the EU sustainable taxonomy. Alessi et al. (2019) estimate the direct exposure of EU non-financial companies to CPRS in 2018 at 37% for their equity and at 33% for their outstanding bonds. The aggregated exposure of the institutional sector in the EU equity market ranges from 30% - 45% in 2018. The institutional bond exposure ranges from 35% - 50%. These large numbers for major European securities indicate the scope of the climate transition given that large parts of the economy are exposed to CPRS.

The results of the CPRS classification were also used to show how shocks to the value of certain financial contracts affected the overall portfolios. Scholars analyzed for example the direct and indirect exposure of European banks, investment funds and other financial actors to CPRS. This classification established the groundwork for a so-called climate stress test, in which 20 EU listed banks are confronted with a hypothetical shock. This shock might for example occur due to unexpectedly ambitious new climate regulation or due to unanticipated low prices for renewable energies. First and second round losses amount from 7% up to 30% of banks' equity. Losses could even be understated as financial actors are embedded in complex financial networks, creating new sources of risk for the economy (Battiston et al., 2017). Other work analyzed the climate transition risk exposure of the European Central Banks current asset purchase program by assigning the bond portfolio into CPRS for each country. In a second step and under weak market neutrality it is shown how the European Central Bank could rebalance its bond portfolio in order to reduce the climate transition risk, measured by the exposure of the bond portfolio to CPRS (Bressan et al., 2021).

2.2 Pricing Models

The theoretical literature on pricing of firms on financial markets always circles around the famous Efficient Market Hypothesis, which states that "security prices at any time `fully reflect` all available information" (Malkiel & Fama, 1970, p. 383). While the hypothesis has been criticized on different grounds (Grossman & Stiglitz, 1980; Guerrien & Gun, 2011) it is still the benchmark approach to pricing in financial markets and its prediction, i.e., that it is impossible for fund managers to consistently beat the market, stands on a solid body of empirical evidence (Fama & MacBeth, 1973; Malkiel & Fama, 1970). But if it is impossible to consistently beat the market through active investing, what role can fund managers play? The answer is given by the widely utilized capital asset pricing model (CAPM), which builds upon the Efficient Market Hypothesis (Pham & Phuoc, 2020). Under standard assumptions of market equilibrium such as efficient capital markets as well as risk averse rational and profit seeking investors (Black, 1972), the CAPM states that there is a linear tradeoff between systematic risk (beta), i.e., the portion of risk which cannot be eliminated by asset diversification and expected return. The CAPM predicts that assets with greater systematic risk than the market portfolio will yield greater expected returns and vice versa. However, on a risk adjusted basis, no outperformance against the market is possible. The CAPM operationalizes this thought through the estimation of an alpha coefficient, which shows potential over/underperformance of a fund against the market. In efficient financial markets the excess return of funds compared to the market average (alpha) is expected to be zero, i.e., no outperformance is possible on a risk adjusted basis. (Black, 1972; Jensen, 1968; Sharpe, 1964, 1966). The role of fund managers thus is not trying to outperform the market but to identify the desired risk level of customers in order to establish a portfolio, which matches the risk tolerance of clients; the return is then just a function of the portfolios systematic risk (Sharpe, 1966).

The initial one factor CAPM model explained stock market variation of portfolios solely by the market factor and was criticized for not being able to capture all of the relevant risk factors. Critiques concluded that the CAPM was therefore not able to explain the cross section of average stock market excess returns over the whole time series sufficiently well (Fama & French, 1992). A famous reformulation of the CAPM is the 3-factor model developed by Fama and French (1993), which adds to the market factor two further risk factors in order to better explain the variation in stock market returns. First, they add the High Minus Low (HML) value premium factor, which accounts for the spread in returns between value (high book to market ratio) and growth (low book to market ratio) stocks. Second, they add the Small Minus Big (SMB) size factor, which considers the return differential between companies with small and big market capitalizations. Comparing the results to the initial one-factor CAPM model Fama and French (1993) found that the estimated model's intercept/alpha was not statistically different from zero for most portfolios anymore. Another interesting tendency observed was that the beta estimate trended towards one for the estimated portfolios. Fama and French (1993) thus conclude that a 3-factor model is better suited in explaining stock market returns since the additional SMB and HML factors can explain why different stocks produce different average returns while the market factor explains why stocks produce excess returns in the first place.

2.3 Pricing of Physical Climate Risks

Climate risk is a new class of risk, which has received increasing attention among scholars (Battiston et al., 2021a). The literature on the pricing of climate risk can be separated into the pricing of physical and transitionary climate risks. Generally, research on the (mis)pricing of climate risk on financial market is still scarce. This is mainly due to the lack of standardized information on the climate risk exposure of companies as well as financial contracts (Battiston et al., 2021a). Concerning *physical climate risk,* Garbarino and Guin (2021) suggest that physical climate risk is underappreciated by market participants in the United Kingdom. Lenders regarded the risk of flooding as a one-time event, which is conflictive with evidence highlighting the danger that increased extreme weather events due to climate change could be the new normal. Similar evidence for the catastrophic bond market shows that climate physical risk is underestimated significantly in this market segment, despite strong evidence for increased risk of Atlantic tornados associated with global warming (Morana & Sbrana, 2019).

Employing a fixed effects panel model, Beirne et al. (2020) show that a country's climate vulnerability has a significant impact on sovereign bond yields. To some limited degree, a nation's relative resilience to physical climate risk can mitigate the effect on sovereign bond yields, highlighting the importance of adaptive investments in countries most affected by climate change. Impulse responses from a structural panel vector autoregression also show that the effect of shocks on climate risk vulnerability and climate resilience is persistent, reaching a peak 15-18 quarters after the shock. This shows that negative consequences from climate change are not a transitionary problem but can potentially impede economic growth in the long run.

Kling et al. (2021) focused on the connection between climate vulnerability to physical risks and companies' cost of capital. Using panel data regressions as well as structural equation models, they find that increased climate related vulnerability goes hand in hand with higher cost of debt, however the authors were only able to show comparable results for firms' cost of equity to a limited degree. Furthermore, the authors state that climate induced risks are set to increase, with companies in developing countries most affected.

2.4 Pricing of Climate Transition Risk

Scholars also compared the pricing of companies more or less exposed to climate transition risk but found equally inconclusive results. By estimating the effect of relevant announcements on carbon intensive or low-carbon stock indices, Monasterolo and De Angelis (2020) find that the Paris Agreement significantly reduced the systematic risk (beta) of low carbon indices, while indices highly exposed to climate transition risks were perceived as riskier than before. However, the overall market reaction for carbon intensive indices was relatively mild, compared to the low carbon ones. These results provide a first tentative hint that financial markets are starting to incorporate climate transition risks and opportunities more heavily after the Paris Agreement. Other related research compared stock performances to German industry averages after the Paris Agreement and found similar results in the short run (Pham et al., 2019).

Mukanjari and Sterner (2018) also focus on the stock market reaction to the Paris Agreement, however they extend the analysis with the 2016 election in the United States (US), which made Donald Trump the 45th president of the United States of America. Utilizing both impulse indicator saturation as well as event study methodologies they find some moderate effects for both events. The Paris Agreement led to some moderate negative abnormal returns for fossil fuel stocks. The election on the other hand only had a significant impact on renewable energy stocks, again the effect is rather small. The authors conclude that the measured effects were smaller than the alleged importance of the major events.

Alessi et al. (2021) focus on the stock market and create a synthetic green indicator for firms, which is based on a 50/50 weighted average between an environmental transparency index and firms GHG emission intensity. They find that greener firms, as measured by their index, have a green risk premium, i.e., investor accept below average returns by green companies since more transparent and less GHG intensive companies are a hedge against future climate risk.

Brammer et al. (2006) find that firms in the United Kingdom exhibiting high scores on corporate social performance indicators underperform the market, while firms scoring worst on the scale significantly outperform the market. By using cross-sectional regressions on stock returns the authors also show that the environmental component in the corporate social indicators is most responsible for the underperformance, while the community aspect is least responsible. A somwehat different message emerges from an older literature review by Renneboog et al. (2007) on socially responsible investment funds, which indicates no statistically significant performance divergence between benchmark funds and mutual funds focusing on socially responsible investments.

However, analyzing the EU emission trading market and using Ordinary Least Squares (OLS) as well as Panel data regressions, Tian et al. (2016) show that rising costs of emission were negatively correlated with stock market returns of carbon intensive energy producers. Stock returns of green energy producers on the other hand profited from rising costs of emissions. Bassen and Rothe (2009) also focus on the EU emission trading market but employ a CAPM approach. They show that carbon is priced as a systematic risk factor since they are able to show that high emitting utilities request a higher carbon risk premium, i.e., their carbon beta estimate is significantly higher than the carbon risk premium for low emitting stocks.

Similar mixed results have been found for the *bond market*. Scholars were able to show a positive effect of green bonds on yields for non-financial institutions as well as supranational institutions. This implies that firms offering green bonds benefit from a lower cost of debt. However, the same finding could not be reproduced for financial institutions, which account for the lion's share of green bond offerings. Additional results indicate the establishment of reputation over time since repeated issuers of green bonds have additional yield benefits compared to one-time green borrowers. Finally, external labelling of a green bond results in a significantly higher green premium compared to self-declared green bonds (Fatica et al., 2021). Zerbib (2019) was able to show similar results. Using a matching method, he estimates a small but significant premium of two basis points for green bonds compared to counterfactual conventional bonds. Karpf and Mandel (2018) on the other hand find that, ceteris paribus, financial markets discriminate against green bonds, when controlling for fundamental economic characteristics of the offering. However, they were able to show that the negative green premium turns positive over time and after 2011 the market rewards green bonds compared to similar conventional contracts.

2.5 The Research Questions

Summing up the literature review on the pricing of climate related risks it can be said that financial markets may have slowly started to price climate risks but overall continue to underestimate the scope and severity of climate risks (Battiston et al., 2019; Battiston et al., 2017). To date, there is no analysis of firms' stock market pricing in financial markets based on companies' standardized CPRS exposure. As opposed to considering indices or industry averages as much of the outlined work did, the CPRS methodology is highly granular and precise on the firm level thus making it an ideal tool to classify firms' climate transition risk exposure. This thesis thus bridges the outlined climate transition risk exposure research strand, which operationalizes the CPRS methodology, with research focused on financial market pricing using the market model in order to analyze the pricing of firms exposed to different degrees of climate transition risk.

It does so by answering two guiding research questions, which reflect the two-part structure of the work. The first research question states:

- *How are global holding companies exposed to climate transition risk?*

Building on the results of the first research question the second research question continuous the inquiry by asking:

- *How is climate transition risk exposure priced by financial markets?*

The thesis thus shows the scope of climate transition risk exposure and its relevance on financial markets. The potential causal transmission channel runs from a firm's climate transition risk exposure as measured by the CPRS classification towards significant differences in pricing on financial markets. Put differently: in the case of a disorderly low carbon transition, the risk exposure of firms might cause significant reevaluations of a firm's value on financial markets as market participants might anticipate falling profitability and stranded assets of fossil fuel related companies (Battiston et al., 2020). If this thesis shows a significant relation between CPRS exposures and pricing, the results will substantiate the causal relation that climate transition risk matters on financial markets.

3. Methods & Data

The research questions are answered with two distinct methodological approaches. The first research question is answered through the establishment of a company database which reclassifies 4-digit NACE codes into CPRS. The section of the thesis answering the second research question uses the generated dataset in order to quantitatively compare the financial market pricing of companies more/less at risk within a disorderly low carbon transition, i.e., with more/less climate transition risk.

Before introducing the detailed methodologies, the key term *climate transition risk*, which was defined in the introduction, must be operationalized. Within the scope of this thesis, firms with high climate transition risk are firms engaged in CPRS 1-6, as they are directly climate policy relevant. Firms in CPRS 7-9 might also be relevant for climate policy, if for example a bank in CPRS 7-Finance exclusively provides loans to coal power plant operating firms. However, their *direct* relevance is limited, thus these firms are not the subject of inquiry for the second research question. Between the CPRS 1-6, CPRS 1-Fossil Fuel is the dirtiest one and thus carries most climate transition risk. The subchapter on the construction of dirty portfolios will go into more detail.

3.1 Methods & Data for Research Question 1

Table 1 and figure 1 show some summary statistics for the full dataset of 1023 companies, which is established in order to answer the first research question. Overall, the highest revenue is earned by JPMorgan Chase with above 150 billion US Dollars, however the dataset also contains many small companies, thus the mean revenue is only 3 billion US dollars. Across the CPRS the `Finance` (7) and `Other` (9) sector are largest in terms of mean revenue, however overall mean revenues for singular CPRS are low as most companies are only engaged in few CPRS. The result section will go into more detail. Almost half of the companies are headquartered in the US, while financial centers such as Great Britain, Switzerland or Hong Kong are also under the top 10 countries in the dataset.

Table 1 | Summary statistics for parent company revenue in each CPRS. *The Table depicts for each of the nine CPRS, the number of observations, the mean revenue per CPRS per company, the respective standard deviation as well as the lowest and highest observation in the sample. Actual revenues can differ as only revenues categorized into CPRS were counted. All numbers, besides observations, are in million US Dollars. Authors' own calculation.*

Variable	Obs.	Mean	Std. Dev.	Min	Max
CPRS1	1023	15	174	0	2985
CPRS2	1023	12	159	0	3060
CPRS3	1023	49	851	0	26275
CPRS4	1023	32	284	0	8012
CPRS5	1023	96	1480	0	36136
CPRS6	1023	1	15	0	361
CPRS7	1023	2258	11049	0	142502
CPRS8	1023	1	10	0	201
CPRS9	1023	283	1463	0	27079
All CPRS	1023	3057	12167	0	156063

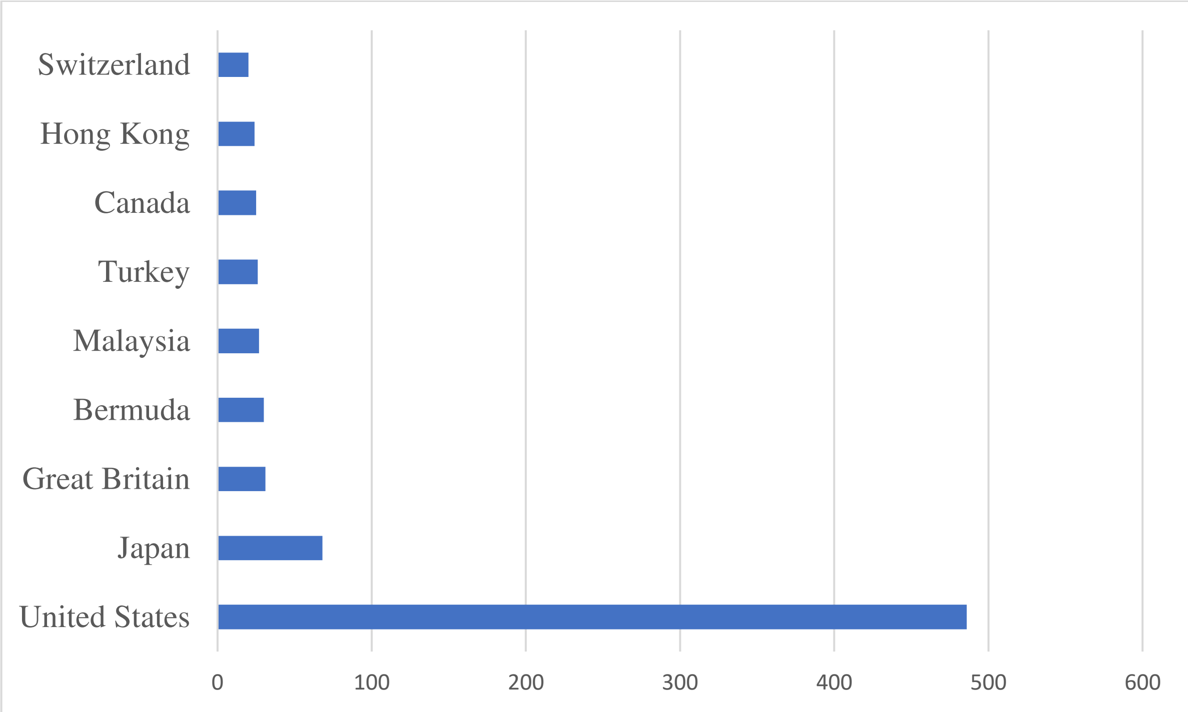

Figure 1 | Top 10 countries in the dataset. *The X-axis illustrates the number of companies, while the Y-axis shows the top 10 countries where the 1023 companies of the dataset are headquartered.*

In order to answer the first research question, this thesis follows the CPRS classification pioneered by Battiston et al. (2017). The overarching goal of step one of the analysis is to classify company revenues into the nine CPRS main groups. This work exclusively focuses on publicly listed, active, and global companies classified as holdings (NACE 64.20), head offices (NACE 70.10), Public relations and communication activities (NACE 70.21) as well as consultancy activities (NACE 70.22) since to date no CPRS classification was performed for this NACE range.

To enable the categorization of holding companies into CPRS, a novel approach, which is solely based on subsidiary revenue information, is developed. This thesis focuses on subsidiaries because they provide a better picture of the real business activities of the parent company since the NACE code of the parent would be classified as `Finance`, whereas the NACE codes of the subsidiaries might unveil that the parent (through its subsidiaries) is actually involved in many very climate policy relevant business activities. Most notably, it is assumed that parent company revenues can be explained by the sum of all subsidiary revenues and that the share of subsidiary revenue in CPRS equals the parents share of business activities in CPRS. More formally, this assumption can be written as:

$$(3.1) \quad \mathrm{RV_i} = \sum_{j=0}^{n} \mathrm{RV_{ij}}$$

Where $\mathrm{RV_i}$ is the parent revenue of company i. $\mathrm{RV_{ij}}$ on the other hand is the revenue of the j'th subsidiary of parent company i. While this assumption simplifies the methodology, it is not always fully accurate because the sum of subsidiary revenues sometimes exceeds the parent company revenue or is significantly lower. This can be explained by the non-consolidated nature of subsidiary revenues and missing revenue information for some subsidiaries respectively.

In line with Lumsdaine et al. (2021), this thesis only considers first level subsidiaries in which the parent possesses more than 50% of ownerships rights. Furthermore, all firms without subsidiary information for at least one subsidiary are excluded since the methodology can only be applied for companies with at least one subsidiary. Finally, companies with zero or negative revenues are excluded.

In order to overcome incomplete subsidiary data and to best use all the available information a novel threefold methodology is introduced, which depends on the relation of parent revenue to the sum of subsidiary revenues:

Case 1:

$$\text{(3.2)} \quad \mathrm{RV_i} < \sum\nolimits_{j=0}^{n} \mathrm{RV_{ij}}$$

If the sum of subsidiary revenues is higher than the parent revenue, the CPRS exposure of the parent company revenue is estimated based on the shares of subsidiary revenues. It is therefore assumed that parents' revenues are well explained by the available subsidiary revenues, because no revenue of the parent company remains unexplained. The surplus revenue on the subsidiary side is most likely explained by the non-consolidated nature of subsidiary revenues which do not eliminate intercompany sales. Thus, it is assumed that the excess subsidiary revenue is equally distributed to the rest of the revenue.

Case 2:

$$\text{(3.3)} \quad \mathrm{RV_i} = \sum\nolimits_{j=0}^{n} \mathrm{RV_{ij}}$$

If the sum of available subsidiary revenue equals the parent revenue, the CPRS exposure of the parent revenue is estimated based on shares of available subsidiary revenues. Again, it seems reasonable to assume that the parents' revenue exposure is well explained by the available subsidiary information since no revenue gaps are apparent.

Case 3:

$$\text{(3.4)} \quad \mathrm{RV_i} > \sum\nolimits_{j=0}^{n} \mathrm{RV_{ij}}$$

If the sum of available subsidiary revenue is smaller than the parent revenue, the CPRS exposure of revenue is also estimated based on subsidiary revenues, however missing subsidiary revenues are estimated using a correctional mechanism. The correctional mechanism uses the revenue gap between parent revenue and sum of subsidiary revenue and distributes it equally to all remaining subsidiaries with available NACE codes but with missing revenue information. In this way, the available industry classification of subsidiaries is not omitted. This approach assumes that the revenue distribution of the remaining parent company revenue can be approximated only by the number of subsidiaries without revenue information in the respective segments.

Finally, for all three cases it is also assumed that the subsidiary revenue with missing NACE codes which had to be excluded is equally distributed relative to the rest of the subsidiary revenue with available NACE codes. However, since there is relatively little subsidiary revenue without NACE classification, this assumption, if violated, should not impair the overall significance of the results. For all three cases, subsidiary revenues are classified into CPRS according to their 4-digit NACE code industry classification in order to estimate the respective climate transition risk exposure of the parents. The classification is based on the work of Battiston et al. 2017 and Battiston et al. 2020 and is performed in an automatic manner due to the large size of the dataset containing roughly 35,000 subsidiaries of 1,023 holding companies. The sum of revenues in each CPRS is then divided by the total revenue of the parent in order to estimate the relative exposure of the parent holding company to each CPRS.

Generally, the results of this methodology are highly dependent on the availability and quality of data on subsidiaries, which are often private and thus associated with significant data gaps. However, this methodology was tested for +20 companies with large subsidiary information gaps by comparing the results from the highlighted methodology with the business segment information from company filings. While the chosen methodology is not 100% accurate, it does reasonably well in approximating CPRS exposure for global holdings, even if large data gaps are apparent. The estimates are better, the more complete subsidiary data is available. Hence the threefold methodology can be regarded as a best guess estimate using all the publicly available information on parent and subsidiary companies. The alternative to this novel methodology is the manual analysis of parent company annual reports, which is too time consuming for such a large quantity of companies, thus the proposed methodology is chosen.

The data for the first part of the research question is retrieved from the databases Orbis (Bureau van Dijk) and Refinitiv Eikon. The databases provide detailed information about company revenues, business lines, subsidiaries, NACE codes and subsidiary revenues. Missing revenue data is augmented by data retrieved from the Eikon database. This thesis utilizes the latest available data for revenues of subsidiaries. This is typically 2020, but in some cases 2019 data was used. Since the climate transition risk exposure is not tracked over time, it is implicitly assumed that the CPRS exposure of holdings remains constant over time. The data can be downloaded directly into Excel sheets, which facilitates further analysis in Excel.

3.2 Methods & Data for Research Question 2

The second part of the research questions is answered building on the CPRS classification of global holdings.

3.2.1 Construction of Dirty Portfolios

In order to test whether the market prices companies' climate transition risk exposure, this thesis constructs various dirty portfolios. Ideally, several portfolios within one CPRS would have been constructed in order to compare companies with clean and dirty energy technologies, e.g., internal combusting engine manufacturers vs. low emission vehicle- or rail companies. However, due to the limited number of companies in CPRS, this thesis concentrates on dirty portfolios with different climate transition risk exposure thereby highlighting different `shades of dirty`.

Portfolios are created based on the revenue exposure in CPRS, utilizing the databank of holding companies established in step one of this thesis. When a company earns above 50% of its revenue in one CPRS it qualifies for being added to a respective portfolio containing this CPRS.

The dirtiest portfolio, bearing most climate transition risk, is constructed by using all companies being predominantly engaged in CPRS 1 – Fossil Fuel, since the very business model of these companies is purely focused on the extraction and production of fossil fuels as primary energy carriers (Battiston et al., 2020). Additionally, companies in CPRS 1 bear significant risk of stranded assets through the massive infrastructure erected to extract fossil energy carriers (Van der Ploeg & Rezai, 2020a). The dirty portfolio bearing less climate transition risk than the very dirty one, is constituted by firms predominantly engaged in CPRS 2 (Utility), 3 (Energy Intensive), 4 (Buildings), 5 (Transportation) and 6 (Agriculture). These sectors often utilize fossil fuels, for example in heat sources for housing or as an energy carrier for industrial processes. However, firms in CPRS 2-6 can switch and diversify to alternative low carbon energy sources more easily than firms in CPRS 1-Fossil Fuels. Thereby they can mitigate the climate transition risk exposure more easily than companies in CPRS 1–Fossil Fuel, whose core business model is the extraction of such energy carriers (Battiston et al., 2020). This thesis also estimates singular portfolios for CPRS 3, 4 and 5 respectively. However, no portfolios consisting of CPRS 6- Agriculture and CPRS 2–Utility were created since only 3 (4) companies are predominantly engaged in CPRS 6 (2) respectively.

For portfolios containing more than one CPRS, i.e., the dirty portfolio, the revenue shares are summed up. If for example a company is earning 33% of revenues in both CPRS 2 and 3 it is still added to the dirty portfolio even though it does not earn above 50% in one CPRS, however the company is not added to the singular portfolios `Energy Intensive` or `Utility`. In total five portfolios are constructed which are summarized in table 2. The Dirty and Very Dirty portfolios are in italics and will be referred to as `baseline portfolios` since the other portfolios are just subsets of the dirty portfolio and the main focus of this thesis is the comparison of portfolios (highly) at risk within a disorderly climate transition. However, as it is difficult to assess whether the Buildings portfolios is more at risk than the Energy Intensive one, no order is presumed for CPRS 2-6 in terms of climate transition risk.

Table 2 | Dirty portfolios utilized for the regressions and description of its constituents*. Authors' own illustration.*

Portfolio Name	CPRS included	Number of companies contained	Examples of activities included
Very Dirty	*CPRS 1*	*9*	*Mining of coal and lignite, extraction of natural gas*
Dirty	*CPRS 2-6*	*115*	*Electric power generation, transmission and distribution, manufacture of motorcycles, real estate activities, air transport*
Energy Intensive	CPRS 3	33	Manufacture of batteries and accumulators
Buildings	CPRS 4	40	Construction of buildings
Transportation	CPRS 5	26	Construction of roads and railways

The firms constituting the various portfolios are weighted in two different ways. First, the portfolios constituents are dynamically weighted based on their monthly market capitalizations relative to the total monthly market capitalization of the portfolio over time. The return for the value weighted portfolio can thus be written as:

$$(3.5) \quad R_{it} = \sum_{j=0}^{n} \omega_{ijt} R_{ijt}$$

With R_{it} being the return of portfolio i at time t, and R_{ijt} the return of firm j of portfolio i at time t. R_{ijt} is calculated with:

$$(3.6) \quad R_{ijt} = \frac{R_{ijt} - R_{ijt-1}}{R_{ijt-1}}.$$

This thesis uses portfolio net returns, because, in contrast to log returns, net returns are portfolio additive, which is useful given that I estimate portfolio returns with the sum operator.

The monthly relative weighting factor of firm j in the value-based portfolio i is ω_{ijt}. ω_{ijt} is calculated through:

$$(3.7) \quad \omega_{ijt} = \frac{MC_{ijt}}{MC_{it}}$$

with MC_{ijt} being the market capitalization of firm j of portfolio i at time t. MC_{it} is the market capitalization of portfolio i at time t.

Second, firms are equally weighted over the whole period t. The weighting factor for portfolio i at time t is then simply:

$$(3.8) \quad \varphi_{it} = \frac{1}{N_{it}}$$

With N_{it} being the number of firms in the respective portfolio i at time t. The return of an equally weighted portfolio is calculated through:

$$(3.9) \quad R_{it} = \varphi_{it} \sum_{j=0}^{n} R_{ijt} = \frac{1}{N_{it}} \sum_{j=0}^{n} R_{ijt}$$

Note that φ_{it} for each portfolio is just a constant, thus it can be excluded from the sum. The return for each equally weighted portfolio is then simply the constant times the sum of firms returns. Since the weighting factor equals $\frac{1}{N_{it}}$, the return can also be regarded as the average of firms returns in each portfolio.

The advantage of an equally weighted portfolio is that it controls for outliers in terms of market capitalization. In the value weighted portfolio some firms dominate portfolios with extremely high market capitalization compared to the other constituents. However, the equally weighted portfolio gives higher weights to smaller firms, which very often have more incomplete stock market data. Thus, the baseline estimates are performed with value weighted portfolios.

3.2.2 Estimation of Several Market Models

In order to compare the pricing of different dirty portfolios on financial markets, this thesis estimates a CAPM since the CAPM is still the benchmark approach for portfolio pricing analysis on financial markets. The CAPM estimates an asset's systematic risk (beta) by means of an OLS time series regression. More formally, the market model is estimated through the following equation:

(3.10) $R_{it} - RF_t = \alpha_i + \beta_i(RM_{kt} - RF_t) + \epsilon_{it}$

R_{it} is the return of the CPRS based dirty portfolios in time period t, calculated trough either (3.9) or (3.5). One time period t corresponds to one month in the time series. The whole time series starts in January 2010 and continues until the most recent available data which is June 2021. So, in total 138 different time periods are utilized for the time series regression equaling exactly 11.5 years. RF_t is the risk-free rate of return, approximated by the 1 Month US Treasury Bill Rate. $R_{it} - RF_t$ is thus the excess return of the constructed dirty portfolios at time t. RM_{kt} symbolizes the return of market portfolio k at time t. Again, it follows that $RM_{kt} - RF_t$ is the excess return of market portfolio k against the risk-free rate. This thesis uses multiple market portfolios, but since the dataset contains global companies, the Morgan Stanley Capital International (MSCI) world index will be the baseline market portfolio. Due to highly sparse dividend data availability and portfolios containing many small companies, dividend returns were not added to the total returns as this would skew results towards larger firms with better dividend data availability. But since the MSCI world index also excludes dividends, comparisons are still valid.

α_i and β_i are time invariant stationary parameters, which are estimated through formula (3.10). α_i is Jensen's alpha coefficient, estimated for portfolio i. The alpha coefficient is the intercept of the regression. Alpha is positive if one of the portfolios outperforms the market on a risk adjusted basis and negative if a given portfolio underperforms the market. If the portfolio performs in line with the market, alpha will be zero, i.e., the regression line runs through the origin. The beta coefficient measures the systematic risk of portfolio i against the market. $\beta_i = 1$ implies a systematic risk of portfolio i in line with the market portfolio, and $\beta_i > 1$ a larger systematic risk than the market portfolio. Notably, both α_i and β_i are time invariant, thus they do not come with the subscript t. Finally, ϵ_{it} is the serially uncorrelated random error term with:

(3.11) $E(\epsilon_{it}) = 0,$

(3.12) $V(\epsilon_{it}) = \sigma^2$

(Jensen, 1968; Pham & Phuoc, 2020).

Additional to the one factor CAPM model, a Fama French 3-Factor Model is estimated through the following equation:

(3.13) $R_{it} - RF_t = \alpha_i + \beta_{1i}(RM_{kt} - RF_t) + \beta_{2i}SMB + \beta_{3i}HML + \epsilon_{it}$

Both the HML and SMB additional factors are estimated through two further beta coefficients for each respective portfolio, the rest of the coefficients and its properties remain unaltered (Fama & French, 1993).

In order to test the significance of the coefficient estimates, simple t tests are performed. The common significance level is, if not specified differently, 0.05.

In addition to the aforementioned models, which incorporate the whole time frame, this thesis also estimates rolling regressions in order to analyze the evolution of estimated coefficients over time. A rolling regression applies a specific time window over the time series dataset and repeats the regression with the constant window moving up in time until the end of the time series is reached. A two year / 24 - month time window is utilized, but different time windows yielded roughly comparable results.

This thesis also performs a Chow Test (Chow, 1960), in order to test for the existence of a structural break in the regressions after the Paris Agreement, which constituted a key global climate policy announcement, in line with Monasterolo and De Angelis (2020). This is permissible as the Paris Agreements impacts could not have been priced into assets prices as the agreement was a surprise for most observers. The date for the suspected break is January 2016 since the Agreement was adopted on the 12th of December 2015. Sometimes a structural break occurs if information about certain policy changes is public before adoption or if public announcements are made in advance. However, since the adoption of the Paris Agreement was a surprise, the Paris Agreement is treated as an exogenous shock and the suspected break point is put directly after the Agreement. This thesis tests for structural breaks in the slope/beta parameter, the intercept/alpha as well as for the whole model. However, structural breaks in the beta coefficient, i.e., the level of systematic risk, after the Paris Agreement are of most interest.

3.2.3 The Time Series Data

The time series data for stock notations, the index notations and the data on market capitalizations were retrieved from Refinitiv Eikon, however some data gaps were filled using the Orbis databank, wherever possible. The monthly data for the Fama French 3-Factor Model as well as the risk-free rate of return were retrieved from Ken French's Website[1]. All computations were performed in Microsoft Excel and Stata.

The dataset of global holding companies contains many small companies and missing/incomplete data on stock returns was a severe issue. Thus, companies with more than one year of missing monthly returns were excluded. Small data gaps were interpolated (if possible) by utilizing the linear function in Excel. Likewise, the data on market capitalization was also incomplete, similarly to the stock market returns, data was interpolated, thereby utilizing a maximum of available information. After all interpolations and exclusions, the universe of relevant companies for the CAPM regressions included 124 companies operating predominantly in CPRS 1-6.

Table 3 highlights key descriptive statistics for the time series data, answering the second research question. The mean return is positive for all portfolios and indexes illustrating the good stock market performance of the last decade. However, some portfolios (dirty, Energy Intensive) or indexes (Fama French market factor or Standard & Poor's (SP) 500) shows higher mean returns compared to other portfolios or indexes. Naturally, larger portfolios are more diversified and thus show a lower variation compared to singular CPRS portfolios such as the Energy Intensive one, which exhibits the highest standard deviation in the sample. Generally monthly returns vary widely from -37% for the very dirty portfolio to a performance of +83% monthly for the Energy Intensive portfolio. Again, the smaller the portfolios, the more extreme the monthly returns. Not surprisingly, the monthly net returns of the market indexes show considerably lower volatility as well as extreme returns.

[1] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

Table 3 | Summary statistics for stock return time series. *The Table depicts descriptive statistics for the net monthly excess stock returns of several constructed portfolios as well as market indexes. Portfolio data is in the first seven rows, index data in the next four and the last two rows indicate data for the two Fama French Factors HML (high minus low) and SMB (small minus big). If not otherwise specified, all portfolios are value weighted. All portfolios and indexes are corrected with the risk-free rate of return, thus highlighting monthly net excess returns. Mean, standard deviation, minimum and maximum are all displayed as percentage returns. Authors' own calculation.*

Portfolio/Index	Obs	Mean	Std. Dev.	Min	Max
Dirty	138	.011	.058	-.275	.338
Dirty (equally)	138	.015	.055	-.205	.327
Very Dirty	138	.005	.054	-.372	.227
Very Dirty (equally)	138	.005	.079	-.292	.427
Energy Intensive	138	.014	.096	-.239	.829
Buildings	138	.011	.065	-.261	.544
Transportation	138	.008	.064	-.329	.297
MSCI World	138	.004	.043	-.147	.126
Euro Stoxx 600	138	.001	.04	-.16	.136
SP 500	138	.007	.041	-.137	.127
FF French Market	137	.012	.042	-.134	.137
SMB	137	.001	.024	-.05	.072
HML	137	-.003	.028	-.14	.082

3.2.4 Regression Diagnostics

This work also tests the time series dataset for common OLS assumptions. While multicollinearity was no issue in a one factor market model, there are some outliers in terms of valuation and stock returns. The extreme stock movements were kept in the dataset as they are part of financial market trading. More problematic are the outliers in terms of market capitalization as some companies dominate the portfolio compositions. A good example is the Porsche SE holding with a current market value of almost 30 billion $, which corresponds to roughly 15% weight of the dirty portfolio and even roughly 30% of the singular Transportation portfolio. While this is a heavy weight, there was no basis to exclude such highly weighted companies. As a stability test to the results, this thesis also presents an equally weighted portfolio in order to control for outlier companies with extreme weights. The OLS regression also assumes a linear relation between dependent and independent variables. This assumption seems very valid as scatter plots between market- and portfolio returns are highly linearly related. Omitted variables are always a problem in econometrics, however, usually there is no easy solution to fix this. While the standard CAPM model is rather basic with only one explanatory factor variable, this thesis also presents the Fama French 3-Factor Model to account for potentially important other explanatory variables.

The gravest problem for the regression was posed by the heteroscedasticity of most portfolio datasets, thereby violating the homoscedasticity assumption of standard OLS. In case of detected heteroscedasticity, Heteroscedasticity and Autocorrelation Consistent standard errors were employed in order to guarantee efficient coefficient estimates. Finally, the regressors in the baseline CAPM model are highly diversified stock market indexes composed of many companies, which are in the case of the MSCI world index even globally distributed. This should weaken potential correlation with the stochastic element of the model.

4. Results

In what follows the results of this work are presented in order to answer both research questions on the climate transition risk exposure and on its implications for financial market pricing.

4.1 Climate Transition Risk Exposure of Global Holdings

The dataset at hand includes global holding companies, which are engaged throughout a variety of economic activities. The merit of this thesis is to break down the economic activities of holdings into as much detail as possible, thereby going beyond the categorization of holdings as purely financial and not directly climate relevant. Through the subsidiary approach, the revenues of holding enterprises can be categorized into CPRS to a high degree of accuracy. The following two figures help better understand the revenue distribution of holding companies and thereby provide an answer to the first research question, i.e., the climate transition risk exposure of holding companies as measured by CPRS exposure.

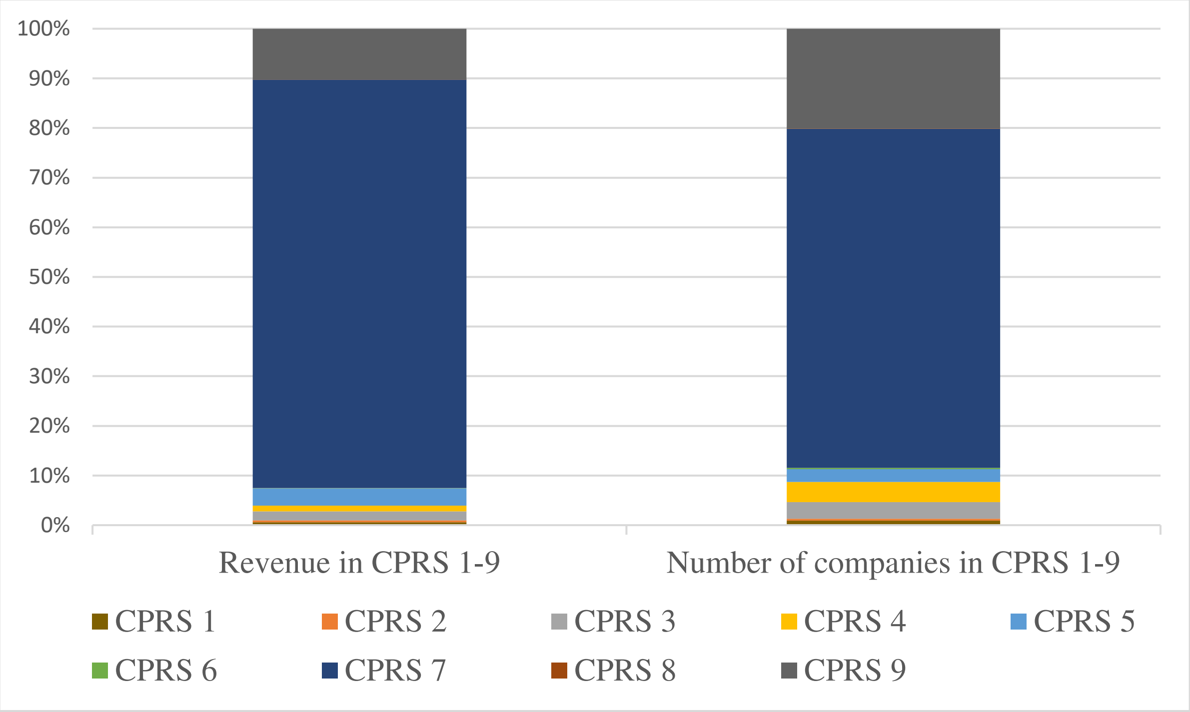

Figure 2 | CPRS exposure of global holding companies*. The left bar indicates the percentage distribution of revenues into CPRS of all companies contained in the dataset. The right bar highlights the percentage distribution of the number of companies being predominantly engaged (>50%) in one CPRS. Again, the bar features all companies contained in the dataset. Authors' own illustration.*

In figure 2 the climate transition risk exposure, measured by CPRS exposure, of the whole dataset of 1023 holding companies is portrayed. Most notably, most holdings are engaged in CPRS 7 - Finance, which is expectable given that the dataset contains many large financial conglomerates such as HSBC or Wells Fargo. However, there is also significant revenue in other sectors, for example 10% of all revenues and even 20% of all firms are engaged in CPRS 9 – Other. The third largest CPRS in terms of revenue is CPRS 5 – Transportation with 3.5%. While 4% of all companies in the dataset are categorized as CPRS 4 – Buildings, they only represent 1% of all revenues, indicating that many companies in CPRS 4 generate below average revenues. The other CPRS are comparably small, both in revenue as well as in number. Adding the results for CPRS 1-6, it can be said that 7.5 % of all revenues are earned in these

CPRS. In terms of company number, 12% of firms earn their revenues predominantly (>50%) in CPRS 1-6.

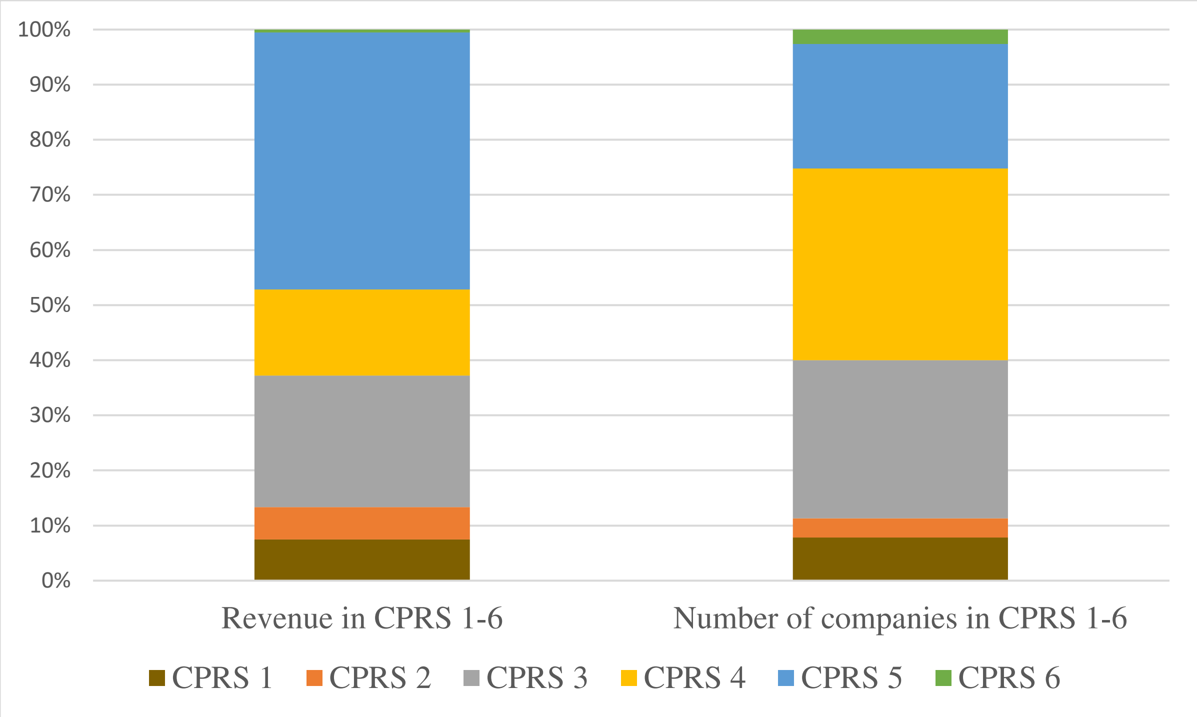

***Figure 3 | CPRS 1-6 exposure of global holding companies**. The left bar indicates the percentage distribution of revenues in CPRS 1-6 of all companies contained in the dataset. The right bar highlights the percentage distribution of the number of companies with above 50% revenues in CPRS 1-6. Authors' own illustration.*

Figure 3 zooms into CPRS 1-6, which are the focus of this work. Again, companies risk exposure is highlighted in terms of revenue as well as in terms of number of companies predominantly engaged in certain CPRS. The 7.5% of total revenue earned in CPRS 1-6 is focused in CPRS 5 – Transportation (47% of CPRS 1-6 revenue) and to a lesser degree in CPRS 4 – Buildings (16% of CPRS 1-6 revenue) as well as CPRS 3 – Energy Intensive (24% of CPRS 1-6 revenue). CPRS 6 is negligible in terms of revenue, CPRS 1 and 2 stand for 8% and 6% respectively.

Interestingly, the 12% of companies with above 50% revenue generated in CPRS 1-6 are more equally distributed, highlighting the concentration of few very big companies in CPRS 5. An example is the International Consolidated Airline group, with British Airways as a top subsidiary generating large revenues. The largest number of companies is engaged in CPRS 3-5, 40 companies earn most revenues in CPRS 4 – Buildings, 33 in CPRS 3- Energy Intensive and 25 in the Transportation CPRS. Only few companies earn the majority of revenues in CPRS 1,2 and 6. Such informative and detailed revenue exposure would be lost if all holding companies were simply assigned to CPRS 7 – Finance.

4.2 Pricing of Climate Transition Risk on Stock Markets

Building on the climate transition risk exposure results, the pricing of dirty portfolios, as highlighted in the method section, can be compared in order to answer the second research question. The results section contains different subchapters. First, the pricing of the baseline portfolios containing the CPRS 1, as well as CPRS 2-6, is compared against market indexes. In the following section, the same exercise is repeated for some singular portfolios. Further sections extend the analysis to the Fama French 3-Factor Model, perform rolling CAPM regression and finally test the time series data for a structural break point after the Paris Climate Agreement.

In order to sort the results and to operationalize the second research question, this thesis will work with five testable hypotheses, which together answer the question whether the financial market is pricing climate transition risk into stock market prices or if the climate transition risks are mispriced/ignored by financial markets. They can also be seen as expectation for an efficient market, because such a market would price all information about climate risks immediately into security prices (Malkiel & Fama, 1970).

- *Hypothesis 1: Very dirty firms exhibit a higher beta than the market average.*
- *Hypothesis 2: Dirty firms exhibit a higher beta than the market average.*
- *Hypothesis 3: Very dirty firms exhibit a higher beta than dirty firms.*
- *Hypothesis 4: Very dirty firms exhibit a strongly rising beta value over time.*
- *Hypothesis 5: Dirty firms exhibit a rising beta value over time.*

4.2.1 Baseline Portfolios against Market

The two baseline portfolios are best suited to test the hypotheses. The baseline very dirty portfolio consists of very GHG intensive fossil fuel companies while the dirty portfolio across the CPRS 2-6 mostly contains companies utilizing fossil fuels. Results for the CAPM regression for the dirty portfolio against several market factors can be observed in table 4.

Table 4 | CAPM regression results for the dirty portfolio. *The column headers highlight different dirty portfolios and its weighting methodology. The rows illustrate the regression results for several market factors and the constant. The last two rows show the number of observations as well as the estimated R squared. Robust standard errors are in parentheses. The significance levels are: *** p<0.01, ** p<0.05, * p<0.1. Authors' own calculation.*

VARIABLES	(1) Value Weighted Dirty Portfolio	(2) Equally Weighted Dirty Portfolio	(3) Value Weighted Dirty Portfolio	(4) Value Weighted Dirty Portfolio	(5) Value Weighted Dirty Portfolio
MSCI World	1.034***	0.734***			
	(0.128)	(0.0913)			
FF Market Factor			1.005***		
			(0.0829)		
Euro Stoxx 600				1.095***	
				(0.126)	
SP 500					1.034***
					(0.134)
Constant/Alpha	0.00736**	0.0125***	-0.000784	0.0102***	0.00443
	(0.00321)	(0.00389)	(0.00361)	(0.00326)	(0.00339)
Observations	138	138	138	138	138
R squared	0.569	0.322	0.519	0.563	0.530

As depicted in the regression output for the value weighted dirty portfolio, the market factor can explain large parts of the variation in excess stock returns of the dirty portfolio. This is highlighted by the R squared of 0.57 for the MSCI world index, indicating that the dirty baseline portfolio is reasonably diversified albeit not as diversified as the market index. The intercept, or Jensen's alpha, is significantly positive on a 5% level, which implies that the dirty portfolio outperformed, on a risk adjusted basis, the market index. The market regressor or the beta coefficient of 1.03 is highly significant on all common levels, however since the CAPM predicts a beta value of one, the key questions is rather whether the beta coefficient is significantly different from 1. Thus, every regression is always combined with a t test of the beta coefficient against the null hypothesis that beta equals 1. For the dirty portfolio this hypothesis cannot be rejected, implying thus that the portfolio is exposed to similar systematic risk levels as the market portfolio.

Table 4 also compares the CAPM regression results for the dirty portfolio against other market indexes, namely the Fama French Market factor (using all stocks listed on New York Stock Exchange, American Stock Exchange, or NASDAQ), the Euro Stoxx 600 and the SP 500. The results are all roughly comparable to the MSCI world baseline market index. Most notably, the dirty portfolio significantly outperforms the Euro Stoxx 600 index, as measured by Jensen's alpha, which is highly significant and positive. These results are not observable for both the Fama French Market factor and the SP 500 as the intercept is not significantly different from zero for both indexes. This result can be easily explained by the outperformance of American stocks, against European stocks as indexed in the Euro Stoxx 600 in the last decade. Thus, while the dirty portfolio is able to outperform a European and Global stock market index, it cannot outperform any American index over a 10-year time span. As already observed in the baseline CAPM model, the beta is not significantly different from 1 for any other stock market index. Finally, the R squared values are all roughly comparable to the baseline regression results.

A different message emerges from the equally weighted dirty portfolio. While the alpha/intercept estimate again is significantly positive on all common significance levels, the beta coefficients is now also significantly below 1, implying below market risk for the equally weighted portfolio. Interestingly the R squared is saliently lower (0.32) than the R squared of the value weighted portfolio (0.57). This sizable lower explained variation in the dependent variable might be a reason for the somewhat surprising result that the beta coefficient is below 1, as the model does not seem to do a good job in explaining the dependent variable. As outlined before, the equally weighted portfolio does also give more weight to smaller companies, which have worst data availability, also potentially explaining the strong difference in results.

Table 5 | CAPM regression results for the very dirty portfolio. *The column headers show several very dirty portfolios and its weighting methodology. The rows illustrate the regression results for several market factors as well as the constant. The last two rows show the number of observations as well as the estimated R squared. Robust standard errors are in parentheses. The significance levels are: *** p<0.01, ** p<0.05, * p<0.1. Authors' own calculation.*

VARIABLES	(6) Value Weighted Very Dirty Portfolio	(7) Equally Weighted Very Dirty Portfolio	(8) Value Weighted Very Dirty Portfolio	(9) Value Weighted Very Dirty Portfolio	(10) Value Weighted Very Dirty Portfolio
MSCI World	0.707***	1.077***			
	(0.191)	(0.170)			
FF Market Factor			0.714***		
			(0.196)		
Euro Stoxx 600				0.720***	
				(0.217)	
SP 500					0.740***
					(0.198)
Constant/Alpha	0.00205	0.00107	-0.00403	0.00384	-0.000367
	(0.00413)	(0.00531)	(0.00508)	(0.00397)	(0.00440)
Observations	138	138	138	138	138
R squared	0.312	0.334	0.309	0.286	0.320

As depicted in table 5, the CAPM time series regression for the value weighted very dirty portfolio of fossil fuel companies yields interestingly different results compared to the dirty portfolios. Most notably the alpha or intercept of the portfolio is not significant on any significance level for the MSCI world market factor. This implies that the very dirty portfolio does not generate excess returns adjusted for the market risk. While the beta or market regressor appears to be low, it is not significantly different from 1, when controlling for the heteroscedasticity of the data. This result indicates that the very dirty portfolio exhibits a comparable sensitivity of portfolio returns to systematic risk as market returns. Furthermore, the R squared of just 0.31 is lower than for the value weighted dirty portfolio, which is expectable as this portfolio contains considerably less companies and is thus less diversified. Comparable results are also obtained for the equally weighted portfolio.

Again, the stability of results is tested by running the same CAPM regressions against the three other market factors, i.e., the Fama French Market, the Euro Stoxx 600 and the SP 500. Every time and in line with the previous results for the very dirty portfolio, the beta is not significantly different from 1 and the alpha not different from zero. This is in line with theoretical expectations, but not necessarily expectable given that these companies are subject to the highest climate transition risk.

4.2.2 Singular CPRS against Market

Beyond the two baseline models, CAPM time series regressions for all other value weighted singular CPRS portfolio are estimated, if there is enough company information available, i.e., for the portfolios constituted by the CPRS 3,4 and 5.

Table 6 | CAPM regression results for the Energy Intensive, the Buildings and the Transportation portfolio*. The column headers illustrate the different portfolios and their weighting methodology. The rows show the regression results for the MSCI world index as the market factor as well as the constant. The last two rows show the number of observations as well as the estimated R squared. Robust standard errors are in parentheses. The significance levels are: *** p<0.01, ** p<0.05, * p<0.1. Authors' own calculation.*

VARIABLES	(11) Value Weighted Energy Intensive Portfolio	(12) Value Weighted Buildings Portfolio	(13) Value Weighted Transportation Portfolio
MSCI World	1.239***	0.835***	1.024***
	(0.226)	(0.110)	(0.0930)
Constant/Alpha	0.00864	0.00774	0.00375
	(0.00621)	(0.00471)	(0.00396)
Observations	138	138	138
R squared	0.305	0.296	0.472

Results as highlighted in table 6 indicate no surprising differences between the CPRS and are largely aligned with the dirty portfolio as well as the very dirty portfolio results. Most notably the results are all in line with classic CAPM predictions, i.e., all betas are not significantly different from 1, and all intercepts/alphas are not statistically different from 0. Thereby indicating no significantly different systematic risk figures as well as no risk adjusted outperformance against the market index. Interestingly, this partly contradicts the results for the dirty portfolio, as the alpha was found to be higher than 0 for some market indexes. The R squared, or portion of stock return variation which can be explained by the market, are all lower than in the dirty portfolio ranging from 0.30 for the Buildings and Energy Intensive portfolios to 0.47 for the Transportation portfolio.

4.2.3 The Fama French 3-Factor Model

This thesis also estimates a Fama French 3-Factor Model, which includes two additional explanatory variables beyond the market factor, namely the SMB size factor as well as the HML value premium factor. This model can be seen as a further stability test to the baseline regression results, i.e., the simple one factor CAPM model. In order to make the results more comparable to the baseline CAPM regression, the 3-factor model is altered slightly by not using the market factor proposed by Fama and French, but instead using the baseline market factor of this thesis, i.e., the MSCI world index adjusted for the risk-free rate.

*Table 7 | Fama-French 3-Factor regression results for the dirty and the very dirty portfolio. The column headers show the portfolios and their weighting methodology. The rows highlight the regression results for the MSCI world index as the market factor as well as the SMB and HML factor. The SMB (small minus big) factor captures potential size premia while the HML (high minus low) factor controls for potential value premia. Additionally, the next row shows the regression results for the constant. The last two rows show the number of observations as well as the estimated R squared. Robust standard errors are in parentheses. The significance levels are: *** p<0.01, ** p<0.05, * p<0.1. Authors' own calculation.*

VARIABLES	(14) Value Weighted Dirty Portfolio	(15) Equally Weighted Dirty Portfolio	(16) Value Weighted Very Dirty Portfolio	(17) Equally Weighted Very Dirty Portfolio
MSCI World	0.939***	0.647***	0.593***	1.057***
	(0.101)	(0.0953)	(0.136)	(0.167)
SMB	0.224**	0.228	0.234	0.124
	(0.112)	(0.166)	(0.156)	(0.207)
HML	0.376***	0.323**	0.475*	0.00180
	(0.144)	(0.139)	(0.271)	(0.235)
Constant/Alpha	0.00861***	0.0136***	0.00335	0.00114
	(0.00313)	(0.00385)	(0.00351)	(0.00516)
Observations	137	137	137	137
R squared	0.613	0.363	0.387	0.336

As shown in table 7, results for the CPRS 2-6 dirty portfolio in a 3-factor model are in line with the one factor model results of the baseline regression. While the alpha is significantly positive for both dirty portfolios, the beta is only statistically different from 1 for the equally weighted portfolio. These results might provide a hint that the CAPM one factor regression for the equally weighted portfolio did not suffer from model misspecification or omitted variable bias, since the results were replicated with more relevant explanatory variables. Concerning the two novel factors, the SMB factor is only significant in the value weighted dirty portfolio. The HML factor is highly significant for both dirty portfolio estimates, indicating that there might be a premium associated with value stocks in the dirty portfolios. The R squared is higher compared to the one factor models, which can be expected when one adds more variables to a regression model. However, the adjusted R squared, that is better suited for comparing models with a different number of regressors, is only slightly higher than the one factor model. Comparing the increase in R squared to the one factor model, it needs to be highlighted that the increases are only marginal compared to the large increases observed in Fama and French (1993) when they added the HML and SMB factors.

Results for the Fama French 3-Factor Model for the very dirty portfolio highlight similar patterns albeit with one key difference. Now the beta estimate for the value weighted portfolio is significantly lower than 1. A result which would not be expected, as based on Fama and French (1993) one would rather expect the opposite, i.e., coefficient estimates for beta converge more towards 1 while estimates for alpha converge towards the expected value of 0. Apart from this finding, the alphas remain unsignificant and the adjusted R squared numbers only rise marginally. None of the two novel factors is significant on a 5% level for the very dirty portfolios, providing more evidence that the 3-factor model, for this dataset, is not better suited in explaining the excess returns of the estimated portfolios.

4.2.4 Estimating Rolling Regression Models

Finally, the aforementioned models can also be estimated through rolling regressions in order to account for some potential dynamic effects in the estimated alphas or betas as well as structural breaks after certain key events. Trends in coefficient estimates could inform about potential changes in the perception and pricing of climate transition risks over time. Results for the rolling regression for the value weighted dirty portfolio with a 24-month window are depicted in figure 4 and 5 and indicate a falling alpha and rising beta coefficient over time. Interestingly, the alpha value is approaching the CAPM predicted value of 0 over time, while beta is highlighting a clear upward trend. This is particularly true for the time after the Paris Agreement since beta estimates start to rise strongly in the years thereafter. Since 2017 the beta rose over the predicted value of 1 and the last regression window even yielded a beta over 1.5.

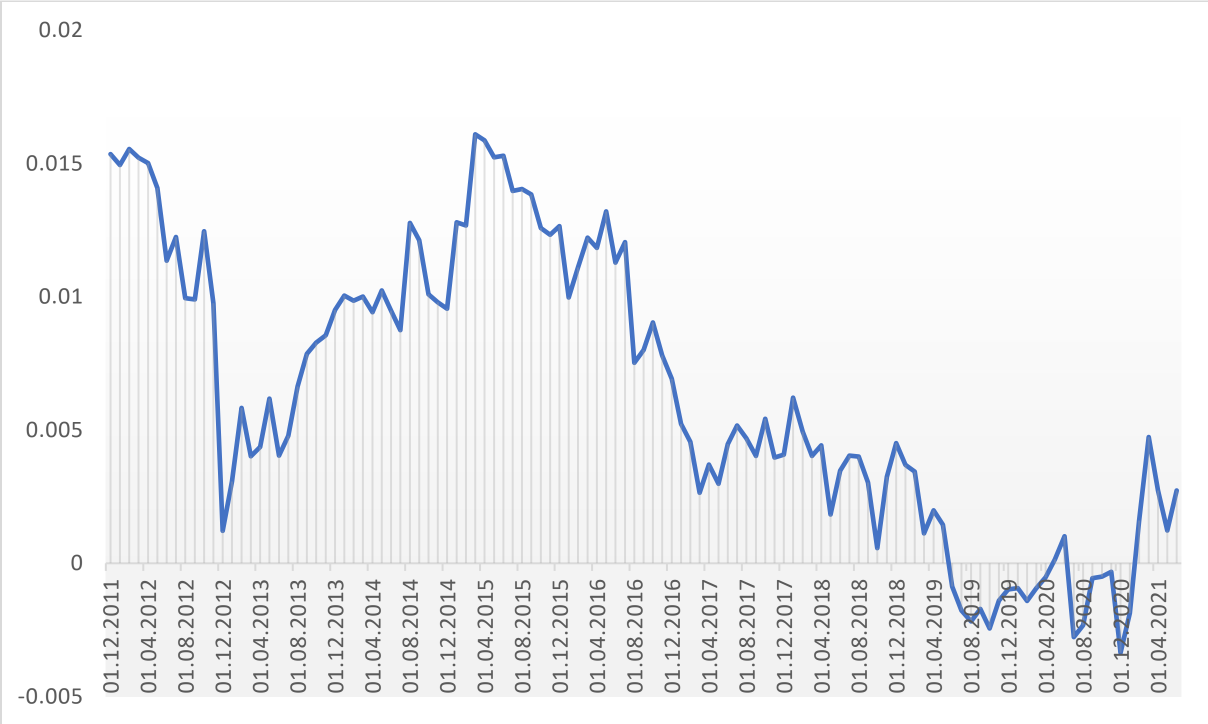

Figure 4 | Alpha Coefficient of the 24-month rolling regression for the value weighted dirty portfolio*. The Y axis shows the value of the estimated alpha coefficient, while the X axis highlights the last date of the 24-month regression window. Authors' own illustration.*

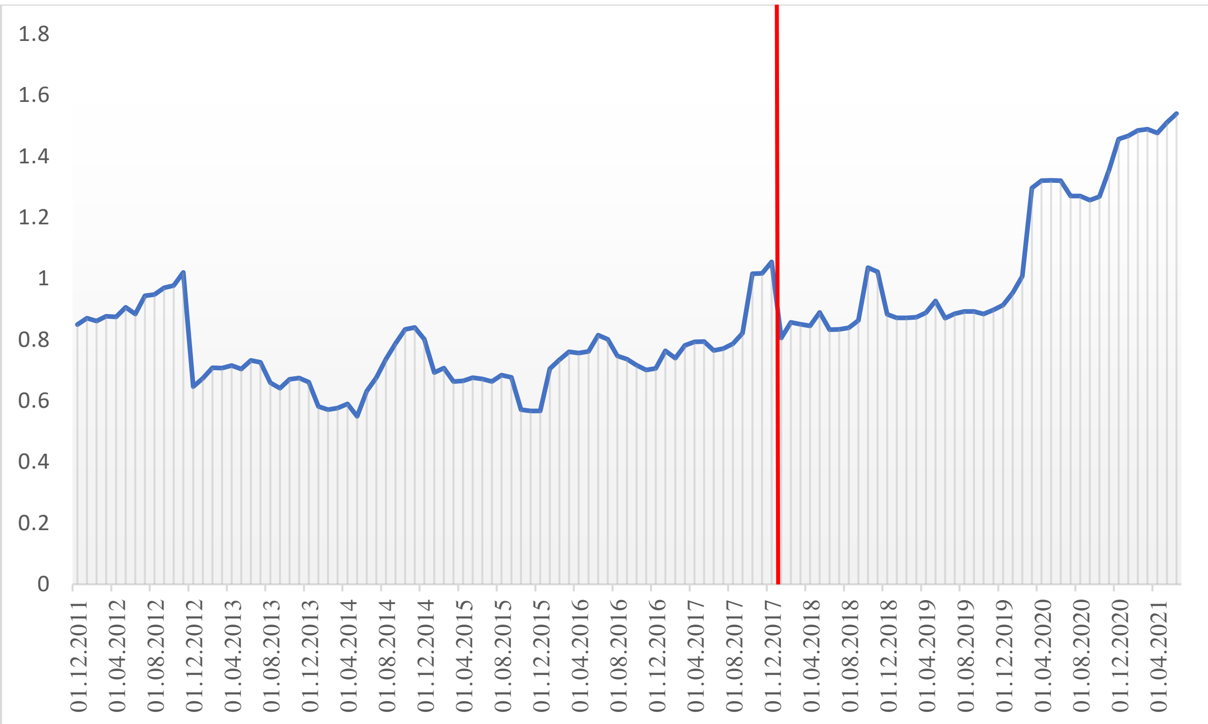

Figure 5 | Beta Coefficient of the 24-month rolling regression for the value weighted dirty portfolio*. The Y axis illustrates the value of the estimated beta coefficient, while the X axis shows the last date of the 24-month regression window. The red vertical line indicates the date when the first rolling regression window incorporates the whole 24 month after the Paris Agreement of December 2015. Authors' own illustration.*

As highlighted in figure 6 and 7, the rolling regression results for the very dirty portfolio (value weighted), directly engaged in fossil fuel activities, show comparable dynamics to the dirty portfolio, however from different bases. The alpha highlights a downward trend over time, starting slightly over 0, and over time decreases below the expected value of 0 in the last rolling regressions. The beta of the value weighted very dirty portfolio shows an even stronger upward trend than the dirty portfolio. While the estimation of beta in the first rolling regression yields a value of 0.20, this estimate rises strongly over 1 and finishes at a very high value of 1.51 at the end of the time series. Again, the Paris Agreement seems to have marked the start of a very strong upward tendency of the beta estimates. Naturally the estimates vary more strongly for the very dirty portfolio, which is expectable, given the reduced number of constituents compared to the larger dirty portfolio.

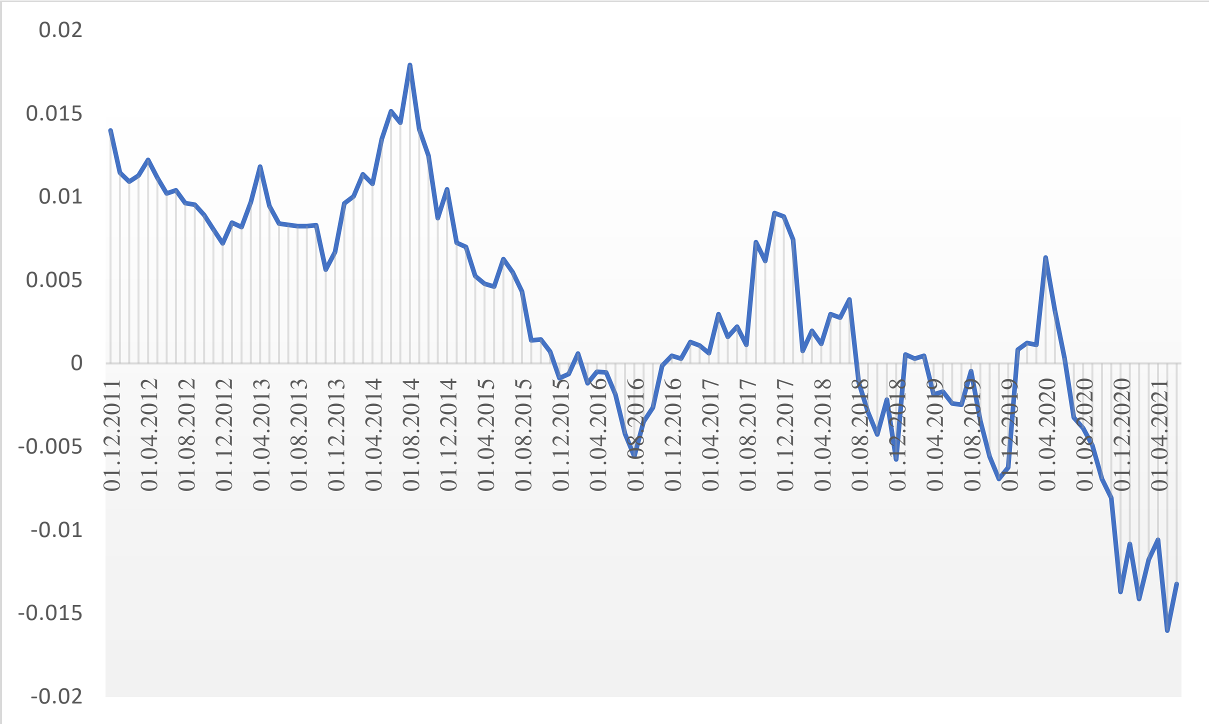

Figure 6 | Alpha Coefficient of the 24-month rolling regression for the value weighted very dirty portfolio*. The Y axis shows the value of the estimated alpha coefficient, while the X axis illustrates the last date of the 24-month regression window. Authors' own illustration.*

Figure 7 | Beta Coefficient of the 24-month rolling regression for the value weighted very dirty portfolio*. The Y axis illustrates the value of the estimated beta coefficient, while the X axis shows the last date of the 24-month regression window. The red vertical line indicates the date where the first rolling regression window incorporates the whole 24 month after the Paris Agreement of December 2015. Authors' own illustration.*

4.2.5 Chow Test for Structural Breaks and Reduced Time Frame Regression

As presented before, the regression coefficients for the CAPM time series regression indicate strong tendencies over time, which are largely consistent throughout the two baseline portfolios. A Chow Test can detect whether the Paris Agreement induced a structural break to the dirty and very dirty portfolios. In other words, whether the Paris Agreement, as a major climate policy shift announcement, triggered a different risk awareness to companies facing high climate transition risk and whether this awareness led to significantly different systematic risk profiles as compared to before the agreement. Results for the Chow Test for both the dirty as well as the very dirty portfolio are roughly similar. For both portfolios there is a structural break after the Paris Agreement for the whole model. More precisely, the structural break is only detectable for the beta coefficient but not for the alpha/intercept of the model, thus providing evidence that the Paris agreement altered the systematic risk assessment of dirty portfolios.

In order to strengthen this argument, this thesis also estimates a reduced time series CAPM model, solely for the timespan after the Paris agreement, since the Chow Test highlighted that the Paris agreement may mark the beginning of a `new era` in the risk assessment of stocks subject to high climate transition risk. Results are highlighted in table 8. The value weighted dirty portfolio indeed shows significantly different estimates compared to the baseline regression over the whole timespan. Most notably, the alpha estimate is now not significantly different from zero anymore, while the beta coefficient now is considerably larger than in the baseline estimate and the beta is even statistically significant over 1.

Table 8 | CAPM regression results for value weighted dirty and very dirty portfolios after the Paris Agreement*. The column headers show the portfolios and their weighting methodology. The rows highlight the regression results for the MSCI world index as the market factor and the constant. The last two rows show the number of observations as well as the estimated R squared. Robust standard errors are in parentheses. The significance levels are: *** p<0.01, ** p<0.05, * p<0.1. Authors' own calculation.*

VARIABLES	(18) Value Weighted Dirty Portfolio after Paris	(19) Value Weighted Very Dirty Portfolio after Paris
MSCI World	1.304***	1.074***
	(0.137)	(0.293)
Constant/Alpha	0.00327	-0.00115
	(0.00377)	(0.00668)
Observations	66	66
R squared	0.792	0.460

The value weighted very dirty portfolio on the other hand, does not indicate different coefficient significances as compared to the baseline estimate over the whole 11.5 year time span. While alpha decreases, it is not statistically different from zero, and while beta increases it is not significantly larger than 1.

Taken together these reduced time series results strengthen the tendency, already observed in the rolling regressions. The sensitivity of (very) dirty portfolio returns to systematic risk (beta) is rising strongly after the Paris Agreement and some portfolios are now reaching a point where the beta estimate is significantly larger than 1, indicating above average systematic risk.

5. Discussion

The following chapter will discuss the results in light of the research questions, integrate the findings in the introduced literature and outline limits of the approach taken. But first, the financial market pricing results are summarized in order to condense a bottom line.

The overall message from the previous portfolio analysis is (despite some inconclusive results) that, over the 11.5-year observation period, the financial market does not price the climate transition risk exposure of companies which are highly exposed to CPRS. In order to simplify the regression results table 9 shows a summary of the most important regression results. While most portfolio estimates exhibit systematic risks in line with the market, some other portfolios are even priced as less risky than the market portfolio. This occurs in two out of three times in the Fama French 3-Factor Model. The estimation results for portfolios containing certain singular CPRS were opposed to the aggregated dirty portfolio since all estimates were in line with predictions from theory. Finally, the Fama French 3-Factor Model estimations also did not add as much explanatory power as expected and mostly replicated the single factor CAPM results. Furthermore, the additional factors were mostly insignificant.

Table 9 | Summary of the main regression results for various dirty portfolios. *For each depicted portfolio the estimated R squared is displayed. The alpha, HML and SMB coefficient estimates are marked as above or below zero if the estimates are significantly different on a 5% significance level. The beta coefficients are depicted as above or below 1 if they are statistically different on a 5% significance level. Authors' own illustration.*

Portfolio Name	**Alpha/Intercept**	**Beta/Slope**	**R squared**	**HML Factor**	**SMB Factor**
Dirty	>0	1	.57	-	-
Dirty (equally)	>0	<1	.32	-	-
Very Dirty	0	1	.31	-	-
Very Dirty (equally)	0	1	.33	-	-
Energy Intensive	0	1	.30	-	-
Buildings	0	1	.29	-	-
Transportation	0	1	.47	-	-
Dirty 3-Factor	>0	1	.61	>0	>0
Dirty 3-Factor (equally)	>0	<1	.36	>0	0
Very Dirty 3-Factor	0	<1	.39	0	0
Very Dirty 3-Factor (equally)	0	1	.34	0	0
Dirty (after Paris)	0	>1	.79	-	-
Very Dirty (after Paris)	0	1	.46	-	-

However, this message changes once the trends in coefficient estimates are regarded over time. Despite some variations, it can be said that the overall systematic risk of both baseline portfolios is rising strongly over time. This is especially true after the Paris Agreement of December 2015, which posed a structural break to the time series for both the very dirty and dirty portfolio. The shorter regressions for the time after the Paris Agreement also highlights higher betas compared to the market average, although this is only significant for the dirty portfolio. The alphas in these restricted regressions also return to the expected value of 0.

Coming back to the five hypotheses formulated in chapter 4, it can be said that hypotheses 1 to 3 could not be substantiated while hypotheses 4 and 5 found support in the rolling regressions results. On the one hand, both the dirty and very dirty portfolios exhibit betas in line or below the market value of 1 for the whole 11.5-year time frame. No portfolio composition, no weighting technique or market factor could produce betas significantly above 1. This strongly indicates that over the whole time frame, the climate transition risk exposure of companies does not play a pivotal role in the pricing of firms on financial markets. This claim is also supported by the rejection of hypothesis 3 since very dirty companies show no significantly higher beta compared to dirty portfolios.

Rejected:

- *Hypothesis 1: Very dirty firms exhibit a higher beta than the market average.*
- *Hypothesis 2: Dirty firms exhibit a higher beta than the market average.*
- *Hypothesis 3: Very dirty firms exhibit a higher beta than dirty firms.*

On the other hand, both hypothesis 4 and 5 could be substantiated by the results from the rolling regressions, the Chow Test as well as the reduced CAPM regressions after the Paris Agreement. Generally, the betas in both portfolios are rising strongly, especially after the Paris Agreement, but the beta for the very dirty portfolio is rising even faster than the beta of the dirty portfolio.

Substantiated:

- *Hypothesis 4: Very dirty firms exhibit a strongly rising beta value over time.*
- *Hypothesis 5: Dirty firms exhibit a rising beta value over time.*

5.1 The Climate Transition Risk Exposure of Holding Companies and its Implication on Financial Market Pricing

The *first research question* can be answered by observing the revenue exposure of global holdings to CPRS 1-6. While the direct revenue exposure to CPRS 1-6 with 7.5% is on average small, it is sizable, and for more than 120 companies, which were the focus of this work, the directly climate policy relevant activities are dominant. Thus, even if the financial system as a whole might withstand distortions from a disorderly low carbon transition, some highly exposed firms face significantly higher climate transition risk, which must be adequately managed (Battiston et al., 2020).

The novel subsidiary-methodology, developed in this thesis, unfolds the business structures of these complex global holdings, and shows in a detailed manner the percentage exposure to each of the nine CPRS. Looking at the overall revenues of all companies in the dataset, most revenues are earned in Finance, which does not automatically imply that these companies are not climate policy relevant. Their *direct* business effects are just not highly exposed to climate transition risk. However, these financial companies could be very well, indirectly exposed to significant climate risks, e.g., through their loans. The analysis of such indirect climate risk was done by others (e.g.: Battiston et al., 2020; Battiston et al., 2019; Battiston et al., 2017) and is beyond the scope of this work. The most important CPRS in terms of direct revenue exposure to climate transition risk are Transportation, Energy Intensive and Buildings. While these CPRS carry climate transition risk through their current use of GHG intensive energy carriers, they could theoretically diversify away from fossil fuels more easily than CPRS 1 – Fossil Fuel. Thus, CPRS 1 – Fossil Fuel clearly carries more transition risk within the context of a disorderly low carbon transition (Battiston et al., 2020). However, the exposure of global holdings to the Fossil Fuel CPRS is, on average, low. Only 0.6% of overall revenues are earned in CPRS 1 and only roughly 1% of all firms are predominantly engaged in this sector.

Since this work focusses on revenues, not on assets, and uses a different dataset, it is not straightforward to directly compare the average exposure to CPRS for global holdings with CPRS exposures found in other work outlined in the literature review. It can be, however, said in general, that the estimated direct exposure to CPRS is lower. Battiston et al. (2020) for example estimate the exposure of Austrian banks to CPRS 1-6 at 26% of all assets. The climate stress test by Battiston et al. (2017) yielded exposures of roughly 45% for Insurance and Pension Fonds and 48% for Governments. Similar to the results of this thesis for global holdings, CPRS 3 - Energy Intensive played an important role.

The value in the first step results is a better disclosure of direct climate transition risk exposure for holding companies which, if classified as `Finance` companies, would fall under the radar of investors trying to assess climate transition risk exposure of their portfolios. "Investors take decisions based on what they can measure" (Monasterolo & De Angelis, 2020, p. 3), thus better disclosure and information on climate financial risks can aid investors in rebalancing portfolios away from companies with significant climate risks, or to ask for higher compensation, which increases the borrowing costs of high-risk companies. Both financial market mechanisms can foster the low-carbon transition (Battiston et al., 2021b).

Building on the results for research question 1, the *second research question* can be answered by comparing the pricing of several dirty portfolios and its evolution over time. The overall results have been introduced in the previous section, but are they in line with an efficient financial market? An efficient financial market values all security prices, at every time, utilizing every information available (Malkiel & Fama, 1970). Since knowledge about the climate crisis, its causes and implications is widely known and available (Stern, 2015), one would expect that climate transition risk is fully factored into market participants expectations and thereby priced correctly into financial markets. An efficient financial market thus prices the climate risk into securities and securities with a higher risk-return profile would be priced with a higher beta value than the market average. The following discussion will focus on the beta factor and only mention results for Jensen's alpha briefly as the beta contains both the mean and the variance of the regression, making it the best tool to compare results for different portfolios.

The results for the *alpha* estimates for the various portfolios are mostly in line with the expected value of 0, thus no risk adjusted overperformance compared to the market factor. However, both the equally and value weighted dirty portfolio exhibit abnormal return over the market on a risk adjusted basis. This extra return usually indicates model misspecification as consistent outperformance of portfolios against the market is extremely rare (Malkiel & Fama, 1970). But even after adding more explanatory factors in the Fama French 3-Factor Model, the estimated alpha remains significantly above 0. This result could potentially indicate, in line with Alessi et al. (2021), that investors demand a risk premium for dirty stocks which are more exposed to climate transition risk. In other words: investors are only willing to invest in riskier dirty stocks if they are compensated with above normal returns. However, the very dirty portfolio performs in line with the market, which runs counter to this argumentation, as the very dirty portfolio should exhibit an even stronger outperformance compared to the dirty portfolio. Thus, the results in terms of alpha are overall inconclusive. Another explanation for the outperformance of the dirty portfolio could be located in the nature of the dataset containing many small companies with incomplete stock market notation, which needed to be interpolated. Thus, measurement errors could cause a bias in the CAPM estimation of Jensen's alpha. This hypothesis is substantiated by the trends of alpha over time, which are falling towards the expected value of zero for both baseline portfolios. Stock market data availability was more complete for more recent years compared to the start of the time series, thus the measurement error might have disappeared in the second half of the time window, when alpha estimates were close to zero for both the dirty- and very dirty portfolio.

Comparing the results for *beta* against theory as well as against the five hypotheses one can assess that, over the 11.5 year period, climate transition risk was not priced by financial markets as the baseline (very) dirty portfolios were priced in line with the market. The equally weighted dirty portfolio even indicates a risk return profile, which is less risky than the market average. These findings also led to a rejection of hypotheses 1-3. Does this imply that financial markets are blind to the carbon risk in companies? Not necessarily, because in 2010, the beginning of the time series, the climate crisis was not at today's critical emergency point and climate transition risk not as central in investors' discussion. Thus, the findings over the 11.5-year period are not necessarily surprising and in line with much work outlined in the literature review which overall did not find that climate transition risks were significantly priced by financial markets (Karpf & Mandel, 2018; Monasterolo & De Angelis, 2020; Mukanjari & Sterner, 2018). It is thus important to observe the trends in beta over time, and the direction of the overall trend in both baseline portfolios is, in line with hypotheses 4 and 5, univocally rising. The beta estimates for the very dirty and dirty portfolio for the time after the Paris Agreement are above 1 and well above the estimates for the time prior to December 2015. This is well in line with what is expected from efficient markets, rising betas as the awareness for climate risks as well as the observable impacts from climate change are more and more obvious (Stern, 2015) and increasingly start to influence investors' expectations. In this regard, the Paris Agreement, which showed the ambition of *all* countries to phase out fossil fuels and fund renewable energies (UNFCCC, 2016), could be an inflection point in the pricing of financial markets as a structural break in the time series was detected for this moment in time. However, as highlighted in the introduction, in the years 2015-2020 many other initiatives such as the Network for Greening the Financial System or the Task Force on Climate-related Financial Disclosures were formed, which in theory all could have led to a higher climate transition risk awareness on financial markets (FSB, 2020; NGFS, 2019).

Despite these signs of a change in the pricing paradigm of financial markets, it must be said that financial markets still underestimate the scope of the climate crisis and its implications on the business models of dirty companies. If humankind wants to have a chance in limiting the impacts from global climate change, companies in CPRS 1 – Fossil Fuel do not have a business model in 10 to 15 years (IPCC, 2021; Carbon Tracker Init, 2017) and are exposed to the significant risk of being left with gigantic stranded assets and large amounts of debt (Carbon

Tracker Init, 2017). The severity of this outlook is not reflected in the beta estimates, which only recently rose above 1 for both baseline portfolios. For the very dirty portfolio, the portfolio most at direct risk within a disorderly transition, the beta estimate is not even significantly higher than 1 after the Paris Agreement, implying comparable risk metrics to the market average.

There are different potential explanation why financial markets understate the risk of companies most exposed to climate transition risk. The most straightforward one relates to the special nature of climate related risks as a novel class of risk, which does not offer past data to base predictions on. Climate related risk is characterized by deep uncertainty, nonlinearity, endogenous perceptions, and long-term stock flow dynamics, which is radically different from common financial risks and thus poses huge problems for traditional risk assessment methodologies (Battiston et al., 2019; Monasterolo, 2020). The relative neglect of the scope and severity of climate transition risks could then be explained by the short, termed nature of the financial market which values firms based on expectations for the next quarters while risk induced by climate change is a very uncertain, nonlinear, and generational issue. Markets are thus ill equipped to price the novel climate transition risk into financial contracts and new risk assessment methodologies, which inform investors about their portfolio risk exposure are direly needed (Battiston et al., 2021a).

For financial market models the finding of a rising awareness for climate transition risks might have interesting consequences because traditional pricing models, such as the CAPM, the 3- or even the 5-factor model might soon not be sufficient to explain stock market variation for high climate transition risk companies. The introduction of an additional `dirty factor` for pricing models, accounting for the rising awareness of investors for climate transition risks, might promise relief. Such a `dirty factor` could be based on CPRS exposure of firms over time. Thereby firms would be differentiated by their climate transition risk exposure and analysts could easily observe whether this factor has a significant impact on portfolio performances. Since CPRS do not only cover activities at risk within a disorderly transition (Battiston et al., 2020), the risk factor could also encompass the potential benefit of a low carbon transition on the business of clean firms.

The aforementioned results of strongly rising betas for both baseline portfolios are clearly relevant for investors because, if the illustrated trends continue, investors highly exposed to CPRS might see the systematic risk levels of their portfolios rise above desired levels. A rebalancing into low carbon investments might decrease systematic risk levels again. The positive effect of adding clean indices to investor portfolios was shown in other work (Monasterolo & De Angelis, 2020).

The findings of this thesis are also relevant from a policy perspective. The results highlight a problematic under awareness of financial markets with respect to climate related risks, especially in the years before the Paris Agreement. Policy makers can regard this as evidence that their climate transition announcements are not fully anticipated by market participants and thus might not be credible enough. However, there are positive signs in the last five years and the adoption of the Paris Agreement might have triggered a structural break in the awareness of investors for climate transition risk. Apparently, the Paris Agreement, to some degree, poses a credible threat to the business model of companies exposed to high degrees of climate transition risk.

5.2 Limits

Despite the relevant findings, some important shortcomings limit the results and lay the ground for further work on the subject. First, the CPRS classification for such a large number of companies with an even larger number of subsidiaries, of which many are not public, was only possible through some justified but strong assumptions. The strongest assumption being that all parent company revenues can be explained by the sum of subsidiary revenues. Another necessary assumption concerned private subsidiaries without publicly available information, which made necessary the outlined 3 case methodology which will only yield roughly correct estimates. Another weakness of the classification is the assumption that CPRS exposure of companies is assumed to be static over time, since only the most recent revenue data was utilized. Taken together these assumptions might bias the results in a particular direction and might well explain some unexpected findings such as the high alpha or low beta value for some dirty portfolios in the first 5 years of the time series.

Second, this thesis only utilizes revenue information in order to estimate the climate transition risk exposure, which is somewhat backward looking, as revenues were already earned when they are reported. Financial markets and rational market participants however look into the future to price firms (Van der Ploeg & Rezai, 2020a).

Third, the chosen dataset of global holding companies did not contain a sufficient number of companies profiting within a climate transition and thus it was not possible to create clean portfolios, which could have been compared against the pricing of dirty portfolios. It was also only possible to create portfolios based on the more aggregated CPRS-Main classification. Datasets with more companies in CPRS 1-6 could be utilized for a more granular CPRS analysis as well.

Finally, the overall data availability in both steps of the analysis was not complete. Especially for the smaller companies, data on subsidiaries, dividends, market capitalizations or stock market returns was incomplete, and interpolations needed to fill some data gaps. This adds some uncertainty to the results.

6. Conclusion

This thesis aimed at answering two questions.

- *How are global holding companies exposed to climate transition risk?*
- *How is climate transition risk exposure priced by financial markets?*

The novel methodology on assessing the climate transition risk exposure of global holdings revealed that, in terms of CPRS, most holdings are not directly subject to large climate transition risk. However, roughly 12% of holding companies face disproportional climate risks, which might unfold in the case of a disorderly low carbon transition, as most revenue is earned through business in highly climate relevant sectors.

With the detailed disclosure of climate transition risks for holding companies, their pricing can be compared against various market portfolios. Results indicate that financial markets still belittle the huge climate related risks for very climate policy relevant firms albeit with changing tendencies. The Paris Agreement seems to mark a starting point for a tentative reorientation of financial market pricing as the systematic risk measures for the dirty and very dirty portfolio rose significantly after the agreement. This also highlights the importance to utilize the most recent data in order to follow recent developments on financial markets.

These findings are relevant due to multiple reasons. They contribute to better disclosure of climate related risks through the detailed CPRS exposure classification of global holding companies with the most recent data. This is particularly important as no CPRS classification was ever conducted for this range of NACE codes. Better disclosure aids investors in rebalancing portfolios and pricing risks correctly. Thereby correct disclosure of climate transition risk might help enable the transition to a low carbon future. Better disclosure is also pivotal for central banks and financial supervisors in order to perform climate stress tests with the best available data (Battiston et al., 2020). Findings gained in answering the second research question aid research on Climate Finance through a novel combination of the CPRS methodology with traditional market pricing models. Results are also clearly relevant for governments in assessing how credible their climate policy announcements are. The tentative evidence of higher climate risk awareness of financial markets indicates that announcements of politicians to phase out fossil fuel in order to become net neutral by 2050 (e.g., in the United Kingdom: Treasury, 2021) are gaining credibility. However, higher carbon prices and a credible commitment for steadily rising carbon prices all the way until 2050 are necessary in order to indicate to financial market participants unequivocally, that the era of fossil fuels is over (Schulmeister, 2020).

There are some interesting avenues for *future research,* which are directly emerging from the aforementioned limits of the chosen methodology. In order to make the CPRS classification more forward-looking one could classify firms Capital Expenditures into CPRS as they lay the ground for future business activities. Another idea would be to change the CPRS classification away from a static approach towards a dynamic CPRS categorization, which would also imply a regular re-composition of portfolios. A logical advancement of this thesis is the construction of clean portfolios. It will be interesting to compare pricing of clean and dirty portfolios, and their evolution over time. A very promising way to construct such portfolios is the comparison of granular CPRS portfolios based on the utilized energy technology within one CPRS-Main group. With a different dataset containing more CPRS 1-6 companies, it would be for example possible to compare two different portfolios within CPRS 5 – Transportation. One could be dirty, e.g., Transportation – Air, while the other one could be clean, containing for example Transportation – Bicycle or Railway. Finally, a very interesting idea for future research is the introduction of a dynamic dirty risk factor to the Fama French Factor Models in order to account for climate transition risk as a novel risk factor, which will increasingly influence stock market returns of firms. Such a dynamic dirty risk factor could be approximated by the CPRS exposure of companies over time.

7. References

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