Climate Change-Related Regulatory Exposure and Corporate Investment Efficiency

Kamrul Huda Talukdar Ph.D. Candidate, Department of Finance, College of Business, University of Central Florida, USA

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Abstract

I identify the effect of climate-change related regulatory exposure on the investment efficiency of US firms. I find that when firms are negatively exposed to regulatory climate risks, they exhibit higher investment efficiency. Furthermore, carbon intensive firms who are subject to higher regulatory risks tend to improve on investment efficiency. Exploiting the Paris Agreement as an exogenous shock, I find that carbon intensive firms' investment efficiency improves following the shock.

Key words: Climate Change, Regulatory Exposure, Investment Efficiency, Overinvestment, Underinvestment

Corresponding Author: Kamrul Huda Talukdar, Department of Finance, College of Business, University of Central Florida, USA, Email: <u>kamrul.talukdar@ucf.edu</u>

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1. Introduction

When exposed to higher climate change-related regulatory risks, does the investment efficiency of firms improve or deteriorate? In this paper, I examine this key question. Considering the impact that capital investment decisions have in driving firm valuation and investor wealth, investment efficiency of firms has been studied widely and is of keen interest to both practitioners and academics. I explore in the same of line of interest, by providing empirical evidence of a previously unexplored nexus between climate change-related regulatory exposure and corporate investment decisions.

As climate change is having a substantial impact globally, in the recent past there is a mounting pressure from investors and regulators on companies to curb their carbon emissions. A recent McKinsey analysis reports that in order to reach net-zero emissions, capital expenditure needs to grow from \$5.7 trillion annually today to \$9.2 trillion annually over the next three decades. The success of decarbonization to a large extent depends on massive new capital deployment and technological innovation. While many have already responded to the brown-to-green transition, more firms are poised to develop new game changing technologies. Anecdotal evidence suggests that, there is a growing number of firms who are spending large amounts of money in adopting sophisticated and risky technologies like Carbon Capture and Storage (CCS), Carbon Dioxide Removal (CDR) and Bioenergy with Carbon Capture and Storage (BECCS). For instance, Exxon has promised to inject billions of dollars into a new business line focused on

what it calls low-carbon technologies such as carbon capture and hydrogen¹. While these firms are responding to the growing societal and regulatory pressures, their capital investment decisions are also subject to deviation from optimal investment levels which is referred to as investment inefficiency according to the literature.

Theoretically, corporate managers are expected to choose projects with positive net present values and make efficient investment decisions (Modigliani and Miller, 1958). However, previous studies find evidence of inefficient investments, namely overinvestment and underinvestment, which are driven by several factors such as adverse selection (Myers and Majluf, 1984), agency problem (Jensen and Meckling, 1976), and managerial overconfidence (Malmendier and Tate, 2005). Information asymmetry between managers and outside investors are believed to justify the agency problem and adverse selection while the managerial overconfidence is due to a behavioral bias. Prior studies document that high-quality financial information can improve investment efficiency by reducing information asymmetry (Biddle et al., 2009, Chen et al., 2011). Furthermore, literature also find that private information acquisition by external market participants, such as institutional investors (Cao et al., 2020), foreign investors (Chen et al., 2017a), and financial analysts (Chen et al., 2017b, Choi et al., 2020). From a monitoring standpoint, better corporate governance (Rajkovic, 2020) and media coverage (Gao et al., 2021) is linked to high investment efficiency. However, the extant literature overlooks how regulatory exposure could affect the managerial capital investment decisions. My paper fills this gap by studying the effect of the climate change-related regulatory exposure on U.S. firms' investment efficiency.

¹ https://www.ft.com/content/b79a9804-4f28-4945-a4bd-1144eb729e78

I choose climate change-related regulatory exposure since it is considered to be one of the important risk factors faced by a firm and affect different firms differently. According to a survey by Krueger et al. (2020) about climate risk perceptions, institutional investors believe climate risks to have financial implications for their portfolio firms and that these risks, particularly regulatory risks, already have begun to materialize. Following the Paris Climate Agreement in 2015, there is a consensus among the participating countries to take actions to limit the temperature increase to 1.5°C above pre- industrial levels. While some can be negatively impacted by the introduction of regulation - e.g. due to increasing operating and input costs - others may benefit - e.g. due to subsidies. Thus, climate change-related regulatory exposure can affect firm's investment decisions.

I contribute to the literature in several ways. First, I extend the literature studying the optimal investment decisions. Second, I contribute to the recent literature on climate finance. Our understanding of climate change related regulatory exposure and corporate investment efficiency is limited, and this study can help explain this puzzle and the investment behavior of firms.

2. Literature Review

Overinvestment problem arises when management can abuse its decision-making power by adopting unprofitable or excessively risky projects that could be against the interests of the stockholders and debtholders (Jensen and Meckling, 1976, Galai and Masulis, 1976, Jensen, 1986, Stulz, 1990). Theoretically, overinvestment problem can take several forms. Jensen (1986) shows how managers prefer to use free cash flow in opportunistic purposes instead distributing then as dividends. With evidence from the oil and gas industry, Jensen (1986) argues that instead of returning the excess cash to the stockholders, the industry continued to spend heavily on exploration and development (E&D) despite lower returns compared to cost of capital.

Furthermore, Stein (2001) connects overinvestment with managerial overconfidence where managers act in good faith with the goal of stockholders' wealth maximization but nevertheless overestimate the their competences and abilities or are overly optimistic about the firms' activities by investing in projects that do not generate a positive NPV.

Firms' investment decision making is a topic studied widely in the finance literature. Bebchuk and Stole (1993), in their study predict that that overinvestment occurs when the market observes the number of opportunities for investment but lacks complete information regarding productivity. Several studies have contributed to the literature striving to explain the firms' overinvestment behavior in the presence of external uncertainty.

According to Semieniuk et al. (2021), transition risks are a combination of three factors namely policy risk, technology risk and preference change. The term policy risk refers to the risks and opportunities that may be caused by climate mitigation policies. Technology risk means the use of cost-saving technologies that would foster the adoption of low carbon energy sources. Preference change indicates the unexpected preference changes in green-motivated costumers' tastes and the unanticipated shifts in investor preferences toward carbon-intensive assets. Li et al. (2020) find that firms facing higher transition risk tend to spend more on capital expenditure in subsequent quarters. Also, they find a negative and significant relation between research and development (R&D) investment and transition risk which implies that the increase in capital expenditure is not driven by their R&D investments. In another study, Cohen et al. (2020) find that firms with lower Environmental, Social, and Governance (ESG) scores, such as oil, gas and energy producing firms are leading innovators in the United States' green patent landscape and yet are explicitly excluded from the ESG funds despite their significantly higher quality green

innovation. In a more recent study, Ahmad et al. (2023) employ a large sample of US listed firms and find that exposure to climate risk is negatively associated with working capital.

3. Data and Methodology

3.1. Empirical Model

The optimal investment level suggests a firm's ability to undertake all positive net present value projects and any deviation from the optimal level indicates inefficient investment. To measure firm level investment efficiency, I follow prior research (Biddle et al., 2009, Benlemlih and Bitar, 2018); who measure firm-specific inefficient investment as a deviation from the expected level of investment. The expected investment is a function of sales growth using the following model.

$$Investment_{i,t} = \beta_0 + \beta_1 Sales \ Growth_{i,t-1} + \varepsilon_{i,t} \quad (1)$$

where, *Investment*_{*i*,*t*} is the total investment for firm *i* in year *t*, calculated as the sum of research and development (R&D) expenditure, capital expenditure, and acquisition expenditure less cash receipts from sale of property, plant, and equipment, scaled by lagged total assets. *Sales Growth*_{*i*,*t*-1} is the annual sales growth rate for firm *i*. The absolute value of the residual term $\varepsilon_{i,t}$ is the investment that is unexplained by growth opportunities, and hence indicates the magnitude of inefficient investment.

I estimate Eq. (1) annually for each industry based on the Fama and French 48-industry classification and require at least 20 observations to be available in an industry-year. From the regression estimates, the absolute value of the residuals multiplied by minus one captures investment efficiency (*INV_EFF*), so a higher value means higher efficiency. I also classify the residuals as overinvestment (*OVERINVESTMENT*) and underinvestment

(UNDERINVESTMENT) for each firm-year based on whether the residual if positive or negative respectively.

Then, I estimate the following regression model:

$$Y_{i,t} = \beta_0 + \beta_1 CCExposure - Reg_{i,t-1} + X_{i,t-1} + \varepsilon_{i,t} \quad (2)$$

where the dependent variable $Y_{i,t}$ equals INV_EFF , OVERINVESTMENT or UNDERINVESTMENT. The main dependent variable, $CCExposure - Reg_{i,t-1}$ is a detailed measure of climate change related regulatory risk at the firm level constructed by Sautner et al. (2023) The measure covers more than 10,000 publicly listed firms from 34 countries and is based on a machine learning algorithm that derives the relative frequency with which bigrams related to climate change occur in the transcripts of the firm's quarterly earnings call. It is constructed on a quarterly basis and then aggregated to a yearly level. $X_{i,t-1}$ denotes the vector of firm level control variables.

To reduce omitted variable bias concerns, following previous literature, I include one year lagged control variables that are considered to be the determinants of firm investment decisions. Among the various control variables, I include *TOBIN'S Q*, to control for firm growth opportunities. Furthermore, inadequate liquidity restricts a firm in undertaking profitable investments. In contrast, excess liquidity could induce wasteful spending. To control for liquidity, I include *CASH*- a ratio of total cash and cash equivalents to total assets, *SLACK*-the ratio of cash and short term investments to net property, plant and equipment. Additionally, investment efficiency could be hampered when firms face difficulties in raising capital. Thus I include *LEVERAGE*, the ratio of total liabilities to total assets. *SIZE* refers to log-transformed total assets. To account for firms' stages in the business cycle I include *ROA* (Profitability)

which is measured by dividing Net Income by Total Assets. *TANGIBILITY* is estimated as the ratio of net property, plant and equipment to total assets.

3.2. Sample Selection and Descriptive Statistics

I obtain firms' financial statement data from Compustat database. Following previous literature, I exclude financial firms (SIC codes 6000-6999) for the sample. For the measure of climate change related regulatory exposure, I use firm level annual climate change exposure data which is available in the database constructed by Sautner et al. (2023). The sample covers U.S. listed firms for the time period ranging from 2002 to 2019. The summary statistics of the key variables are reported on Table 1. Following previous studies, I winsorize all continuous variables at the 1% and 99% levels. The mean investment efficiency across all firm-years equals -0.18. On average, the sample firms possess important growth opportunities as indicated by *TOBIN'S Q* of 2.082 In my sample, the average climate change related regulatory exposure is 0.003 and the standard deviation is 0.02, showing that considerable variation exists in the measure of climate change exposure.

Variables	Observations	Mean	Std. Dev.	Min	Max
OVERINVESTMENT	8172	.208	.165	.021	.519
UNDERINVESTMENT	13264	167	.167	587	029
INV_EFF	21436	18	.161	537	026
CCExposure-Reg (X100)	21833	.003	.02	0	1.022
LEVERAGE	21671	.206	.195	0	.55
TOBIN'S Q	20890	2.082	1.083	.964	4.322
CASH	21780	.246	.221	.013	.659
SIZE	21782	6.428	1.392	4.316	8.659
ROA	21779	02	.138	328	.123
TANGIBILITY	21772	.226	.204	.028	.642
SLACK	21739	3.566	4.808	.037	14.74

Table 1: Descriptive Statistics

4. Empirical Results

4.1. Main Tests

Table 2 presents the baseline regression results of Eq.(2) using ordinary least squares (OLS) with industry and year fixed effects. The standard errors are clustered at the industry level. The main variable of interest is the regression coefficient β_1 , which measures the effect of climate change related regulatory exposure on investment efficiency. In columns (1)-(2) and (3)-(4), the dependent variables are overinvestment (*OVERINVESTMENT*), measured as the positive residuals from Eq.(1), and underinvestment (*UNDERINVESTMENT*), measured as the negative residuals from Eq.(1), respectively. In columns (5)-(6), the dependent variable is investment efficiency (*INV_EFF*), measured as the absolute value of the residuals from Eq.(1) multiplied by minus one, so a higher value means higher investment efficiency. Models (1), (3) and (5) are estimated without controls, but with industry fixed effects (classification based on Fama and French 48 Industries) and year fixed effects. Models (2), (4) and (6) include all the control variables with industry and year fixed effects. Standard errors are corrected for heteroskedasticity and clustered at the industry level.

In columns (1) and (2), the coefficient for *CCExposure-Reg t-1* (X100) is positive and significant at all the significance levels. The results indicate that when firms are exposed with climate change related regulatory risk, overinvestment increases. In columns (3) and (4), the coefficient *CCExposure-Reg t-1* (X100) is negative and significant at 10% significance level, implying that firms' underinvestment increases when they are exposed with climate change related regulatory risks. Combined together, the results in column (5) and (6) show a negative and statistically

significant coefficient for *CCExposure-Reg t-1 (X100)*, which indicates that when firms are exposed to climate change related regulatory risks, their investment efficiency decreases.

	(1)	(2)	(3)	(4)	(5)	(6)
	Overiny	vestment	Underiny	vestment	Investment l	Efficiency
CCExposure-Reg t-1 (X100)	.3261***	.1775***	2097*	1836*	2348***	1519**
	(.046)	(.0644)	(.1127)	(.1047)	(.0701)	(.0709)
TOBIN'S Q t-1		.0145***		0125***		0134***
		(.0035)		(.0024)		(.0021)
LEVERAGE t-1		.0157		0603***		041***
		(.019)		(.0128)		(.0134)
CASH t-1		.04***		.0626***		.019
		(.0137)		(.0195)		(.0138)
SIZE t-1		0292***		.0076***		.0137***
		(.002)		(.0023)		(.0017)
ROA t-1		1311***		.1526***		.1696***
		(.0415)		(.0419)		(.0373)
TANGIBILITY t-1		.0329		.0592***		.0344*
		(.0269)		(.0185)		(.018)
SLACK t-1		.0026**		0044**		0034**
		(.0012)		(.0017)		(.0014)
Constant	.193***	.2937***	1623***	1911***	1713***	2221***
	(.0001)	(.017)	(.0003)	(.0147)	(.0002)	(.0124)
Observations	6677	6393	11167	10681	17846	17076
R-squared	.1657	.2863	.1755	.2164	.1635	.2276
Industry fixed effect	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES

Table 2: Climate change related regulatory exposure and investment efficiency

Standard errors are in parentheses

*** *p*<.01, ** *p*<.05, **p*<.1

4.2. Additional Tests

I employ additional tests to disentangle the effects of positive and negative regulatory exposure on corporate investment efficiency. Firms that consider themselves to be negatively impacted by the introduction of climate change regulation are considered as negatively exposed firms. For these firms, the regulatory changes can negatively affect operating costs, earnings, and cash flows as well as it can relate to an increased loss probability (Huang et al., 2018, Nguyen, 2017). In contrast, certain firms consider themselves to benefit from the regulatory changes, for instance, firms receiving subsidies for greener technologies. These are referred to as positively exposed firms. I use sentiment measures constructed by Sautner et al. (2023) where *CCSentiment-Pos* t-1 is based on the relative frequency with which bigrams related to climate change are mentioned together with positive tone words. Similarly, *CCSentiment-Neg* t-1 is based on the relative frequency with which bigrams related to climate change are mentioned together with bigrams related to climate change are mentioned are mentioned together with bigrams related to climate change are mentioned as follows:

$$Y_{i,t} = \beta_0 + \beta_1 CCSentiment - Pos_{i,t-1} + X_{i,t-1} + \varepsilon_{i,t} \quad (3)$$
$$Y_{i,t} = \beta_0 + \beta_1 CCSentiment - Neg_{i,t-1} + X_{i,t-1} + \varepsilon_{i,t} \quad (4)$$

Table 3 demonstrates the results from eq. (3) and (4). Columns (1) and (4) show that when firms are exposed to positive regulatory exposure, firms' overinvestment increases, whereas for negatively exposed firms, the overinvestment decreases. Columns (2) and (5) illustrate that negative regulatory exposure leads to decrease in firms' underinvestment. Overall, from column (3) and (6), I find evidence that when firms are faced with negative regulatory exposure, investment efficiency improves, the coefficient being positive and statistically significant at 5% level. Whereas, there is little evidence that when firms are faced with positive regulatory shocks, firms investment efficiency deteriorates, the coefficient being negative and statistically insignificant.

	(1)	(2)	(3)	(4)	(5)	(6)
	Overinvestment	Underinvestment	Investment Efficiency	Overinvestment	Underinvestment	Investment Efficiency
CCSentiment-Pos t-1	.3607**	1742	1853			
	(.1611)	(.212)	(.1489)			
CCSentiment-Neg t-1				3361*	.6219**	.4305**
				(.1914)	(.2397)	(.1751)
TOBIN'S Q t-1	.0145***	0125***	0134***	.0145***	0124***	0133***
	(.0036)	(.0024)	(.0021)	(.0036)	(.0024)	(.0021)
LEVERAGE t-1	.0156	0602***	041***	.0156	0603***	041***
	(.019)	(.0128)	(.0134)	(.019)	(.0128)	(.0134)
CASH t-1	.0397***	.0625***	.0192	.0394***	.0625***	.0193
	(.0137)	(.0194)	(.0138)	(.0138)	(.0195)	(.0139)
SIZE t-1	0292***	.0076***	.0137***	0292***	.0076***	.0137***
	(.002)	(.0023)	(.0017)	(.002)	(.0023)	(.0017)
ROA t-1	1314***	.1535***	.1701***	1312***	.1524***	.1696***
	(.0414)	(.0416)	(.0371)	(.0415)	(.0418)	(.0373)
TANGIBILITY t-1	.0328	.0587***	.0342*	.0328	.059***	.0343*
	(.0269)	(.0185)	(.018)	(.0269)	(.0185)	(.018)
SLACK t-1	.0026**	0044**	0034**	.0027**	0044**	0034**
	(.0012)	(.0017)	(.0014)	(.0012)	(.0017)	(.0014)
Constant	.2938***	1917***	2224***	.2943***	1914***	2224***
	(.017)	(.0147)	(.0124)	(.0172)	(.0147)	(.0124)
Observations	6393	10681	17076	6393	10681	17076
R-squared	.2861	.216	.2273	.286	.2165	.2276
Industry fixed effect	YES	YES	YES	YES	YES	YES
Year fixed effect	YES	YES	YES	YES	YES	YES

Table 3: Climate change related regulatory exposure (positive and negative) and investment efficiency

Standard errors are in parentheses

*** *p*<.01, ** *p*<.05, * *p*<.1

4.3. Cross-sectionally heterogeneity

To understand better and to identify the effect of climate change related regulatory exposure on investment efficiency of firms, I rely on cross sectional comparison and further test on whether this effect is stronger for carbon intensive firms following the industry classification employed by Ilhan et al. (2021). Carbon-intensive industries are more exposed to climate regulation and risk (Bolton and Kacperczyk, 2021, Ilhan et al., 2021). I analyze the effect of climate change exposure on carbon intense firms by estimating the following empirical model:

$$Y_{i,t} = \beta_0 + \beta_1 CCExposure - Reg_{i,t-1} * Carbon Intensive + \beta_2 CCExposure - Reg_{i,t-1} + \beta_3 Carbon Intensive + X_{i,t-1} + \varepsilon_{i,t}$$
(3)

In Eq.(3), the *Carbon Intensive* is an indicator variable taking the value of 1 if the firm belongs to one the carbon intensive industries as employed by Ilhan et al. (2021) and 0 for other firms. Table 4 demonstrates the results of regressions as indicated in Eq. (3) run for the carbon intensive industries interacted with the climate change related regulatory exposure. In all the specifications, I control for the year fixed effects. The robust standard errors are clustered by firms.

	(1)	(2)	(3)	
	Overinvestment	Underinvestment	Investment	
			Efficiency	
CCExposure-Reg t-1 (X100)	.2077***	2923***	2364***	
	(.062)	(.0846)	(.0559)	
Carbon Intensive	.0497***	0438***	045***	
	(.0085)	(.0072)	(.0058)	
CCExposure-Reg 1.1 (x100)* Carbon Intensive	0747	.7206***	.448**	
	(.3911)	(.247)	(.2144)	
TOBIN'S Q t-1	.0172***	0137***	0153***	
~	(.0021)	(.0021)	(.0016)	
LEVERAGE t-1	.0352***	0702***	0545***	
	(.0125)	(.0107)	(.0084)	
CASH t-1	.0525***	.0589***	.0131	
	(.0158)	(.0164)	(.012)	
SIZE t-1	0266***	.0058***	.0115***	
	(.0017)	(.0015)	(.0012)	
ROA t-1	1795***	.1861***	.215***	
	(.0171)	(.0222)	(.0138)	
TANGIBILITY t-1	.0659***	.0179	0033	
	(.0145)	(.0111)	(.0094)	
SLACK t-1	.0037***	0054***	0044***	
	(.0007)	(.0008)	(.0006)	
Constant	.2452***	1573***	1826***	
	(.013)	(.0114)	(.009)	
Observations	6458	10766	17224	
R-squared	.2633	.1846	.2005	
Industry fixed effect	NO	NO	NO	
Year fixed effect	YES	YES	YES	
Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1				

Table 4: Climate change related regulatory exposure-cross sectional heterogeneity

From the results, the interaction between climate change related regulatory exposure and carbon intensive firms as indicated by CCExposure-Reg $_{t-1}$ (x100)* Carbon Intensive shows statistically insignificant negative coefficient for column 1 (overinvestment) and statistically significant and positive coefficients for the other two specifications (underinvestment and investment efficiency respectively). This implies that when faced with regulatory exposures, carbon intensive firms' investment efficiency improves. More specifically, I find evidence that carbon intensive firm's underinvestment decreases.

4.4. Quasi Natural Experiment

I conduct a quasi-natural experiment surrounding the Paris Agreement by exploiting the exogenous nature of Pairs Agreement. Following the Paris Agreement, governments are expected to impose more stringent climate changes regulations which is expected to affect firms' investment decisions. I examine the effect of regulatory exposure on firm's investment inefficiency by estimating the following regression:

$$Y_{i,t} = \beta_0 + Carbon Intensive + \beta_1 Paris + \beta_3 Carbon Intensive * Paris + +X_{i,t-1} + \varepsilon_{i,t}$$

$$+ \varepsilon_{i,t}$$
(4)

where *Paris* is an indicator variable taking the value of 1 for the years after 2015 and 0 for the other years. The variable of interest is the interaction term *Carbon Intensive* * *Paris*. The results are reported in Table 5.

Table 5: Paris Agreement as an exogenous shock

	Overinvestment	Underinvestment	Investment Efficiency
Carbon Intensive	.0454***	0429***	0433***
	(.0073)	(.0067)	(.0051)
CarbonxParis	0116	.0266**	.0224***
	(.0122)	(.011)	(.0085)
TOBIN'S Q t-1	.0124***	0122***	0124***
	(.002)	(.0019)	(.0014)
LEVERAGE t-1	.0297***	051***	0411***
	(.0115)	(.0099)	(.0076)
CASH t-1	.0437***	.0459***	.0049
	(.0145)	(.0153)	(.0111)
SIZE t-1	0318***	.0031**	.0126***
	(.0016)	(.0015)	(.0011)
ROA t-1	1922***	.2***	.2322***
	(.015)	(.0197)	(.0122)
TANGIBILITY t-1	.0635***	.0112	0093
	(.0126)	(.01)	(.0083)
SLACK t-1	.0034***	0051***	0041***
	(.0007)	(.0008)	(.0005)
Constant	.3009***	1473***	2027***
	(.0117)	(.0106)	(.0081)
Observations	7779	12646	20425
R-squared	.2554	.1361	.1796
Industry fixed effect	NO	NO	NO
Year fixed effect	YES	YES	YES

Standard errors are in parentheses *** p<.01, ** p<.05, * p<.1

5. Conclusion

I identify the effect of climate-change related regulatory exposure on the investment efficiency of US firms. I find that when firms are negatively exposed to regulatory climate risks, investment efficiency improves. Furthermore, carbon intensive firms who are subject to higher regulatory risks tend to improve on more efficiently. Exploiting the Paris Agreement as an exogenous shock, I find that carbon intensive firms' investment efficiency improves following the shock.

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