Impact of climate policy uncertainty on corporate climate-related investments

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We propose studying the impact of climate policy uncertainty on corporate environmental spending. We base our empirical work on a theoretical model, collect data for the U.S. and find that Climate Policy Uncertainty as measured by a news-based index has no effects on environmental investments. However, these results are not yet reliable. We describe further steps to obtain more robust results.

1 Summary of the idea

As a real-world problem with economic implications, climate deterioration has received extensive attention from the academic circle. Intuitively, climate change will affect the profits and profitability of companies not only through physical factors but also through policy factors such as Pigovian taxes, emission caps, and sustainable investing regulations. A major problem in investigating the impact of climate change on firms is that policies are uncertain. Our idea is to investigate how uncertainty in the government's climate policies influence companies' decisions to invest in green technologies. We start from the theoretical model by Biais and Landier (2022), extract expected empirical relations, and devise an identification strategy given available data. In empirical terms, we use panel data models to examine the effects of news-based climate policy uncertainty on companies' environmental investments and expenditures.

2 Literature review

In this section, we review theoretical and empirical studies on the effects of general policy uncertainty on firms' investment. Then, we focus on the most relevant work on the impact of climate policies and climate policy uncertainty.

There is consensus in the literature that political or policy uncertainty has a negative impact on firms' investment. Theoretically, when there is uncertainty, the option value of delaying investment increases and firms decide to hold back until uncertainty is (partially) resolved (Bernanke, 1983). Recent empirical evidence supports this argument. Julio and Yook (2012) find that firms make substantially less investments in election years compared to in non-election years. Gulen and Ion (2016) use the news-based index by Baker, Bloom and Davis (2016) instead of political events to capture uncertainty and find supporting evidence. Furthermore, they find that the negative relationship between policy uncertainty and capital investment is stronger for firms with a higher degree of investment irreversibility and higher dependence on government spending.

However, whether the theory holds for climate policies is an open question. The majority seems to confirm the wait-and-see hypothesis. An early options model by Fuss, Szolgayova, Obersteiner, and Gusti (2008) shows that uncertainty induces producers to postpone investment and see if the government will actually commit to climate policy. Biais and Landier (2022) take a step further and show that the government's commitment decision and firms' investment decisions are strategic complements. On one hand, the government imposes a cap on emissions if aggregate emissions are low and it is not too costly to impose a cap. On the other, firms invest in green technologies and reduce emissions if they anticipate the cap. Empirical evidence seem to support the real options effect. Noailly, Nowzohour, and van den Heuvel (2022) construct their own news-based environmental and climate policy uncertainty index which is documented to have a negative association with the probability of green startups to be funded by venture capitalists. Yet, Wang (2022) documents opposing evidence: when facing higher policy uncertainty, companies take pre-emptive actions by pushing for innovation, i.e. registering more patents, and by reducing their emissions early on.

We contribute to this literature by inspecting the effects of climate policy uncertainty on investments made by existing firms instead of startups or patents. In this proposal, we will present results using the climate policy uncertainty index, which is widely used by studies mentioned above. However, another contribution would be exploiting policy events to capture uncertainty.

3 From theory to empirics

This section introduces the most relevant features of Biais and Landier's (2022) theoretical model. It is a two-period model with two types of agents: the government and a unit mass of entrepreneurs who own and operate firms. In period 1, a fraction γ_1 of firms decide or not to invest in green technologies with irreversible investment cost c_1: $\gamma_1 = \int_{i=0}^{1} I_i^1 \, di$ where $I_i^1 = 1$ if firm i invests, and = 0, otherwise. All firms emit $e_i^1 = \theta$. Technology developed by firms who invest now will spill over and reduce abatement costs for all firms. In period 2, firms produce output Y and emit carbon $e_i^2 = \theta - 1$ if it did invest in green technologies or emit $e_i^2 = \theta$ if it did not. The government observes aggregate emissions and decide to cap emissions or not, i.e., it will set a value for $\gamma_2 = \int_{i=0}^{1} I_i^2 \, di$, the fraction of firms who are obliged to invest in abatement technologies in period 2. Investment cost for abatement technologies is $c_2 = \kappa - \lambda\gamma_1$ where $\kappa \geq c_1$ reflects time-to-build constraints, λ is the strength of technology spillover effects.

An entrepreneur i does not internalize negative externalities nor positive spillover effects and take γ_1 as given. The government care about environmental externalities and investment costs that firms incur. Solving the first best case in which the government impose investment decisions on firms yields the condition under which it is optimal to cap emissions in period 2 (set $\gamma_2 = 1 - \gamma_1$): the social cost of emissions plus investment costs under the cap is smaller than the social cost of emissions without the cap: $d(\theta - 1) + c_2(1 - \gamma_1) < d(\theta - \gamma_1)$. Substituting $c_2 = \kappa - \lambda\gamma_1$ and simplifying yields

$$\gamma_1 \geq \frac{\kappa - d}{\lambda} \tag{1}$$

which implies that the fraction of firms who invested in green technologies in period 1 must be large enough so that it is optimal for the government to cap emissions in period 2.

In an equilibrium with competitive firms where the government does not observe period-1 investment decisions (γ_1) and so cannot commit to period-2 policies. The government will impose an emissions cap in period 2 with probability μ. Then, firm I will invest in period 1 if

$$Y - \mu c_2 \leq Y - c_1 \Rightarrow Y - \mu(\kappa - \lambda\gamma_1) \leq Y - c_1. \tag{2}$$

When more firms invest early (higher γ_1), it's more attractive for the rest to delay investment due to lower c_2. When the probability of a cap is higher (higher μ), it's more attractive for firms to invest early. Thus, given (1) and (2), firm's period-1 investment decisions and government's period-2 decision to cap are strategic complements.

From an empirical point of view, i.e. taking into consideration available databases and empirical methods, the period-1 relation between the probability of an emissions cap μ and the firms' investment decision I_i is the most testable with a clear theoretical prediction. As an emissions cap becomes more likely (higher μ or lower CPU), firms are more likely to invest in green technologies.

The key parameters can be estimated empirically as follows:

- μ, the probability of an emissions cap, can be estimated with the Climate Policy Uncertainty (CPU) index that proxies for how certain or uncertain climate policies will be passed and implemented;
- e_i's empirical version is straightforward as emissions data are provided by many ESG data providers;
- I_i, the firm's decision to invest in green technologies can be directly measured using Eikon Refinitiv's data on Environmental Investment Initiatives, an indicator of whether a company has an environmental investment or not;

In the following sections, we will describe in details the data sets and methods and report preliminary results. Since the CPU index, our proxy for μ is readily available for the U.S., we will report preliminary results using a sample of firms located in the U.S. A European Union sample is equally interesting given the implementation of the EU Emission Trading Scheme.

4 Data and summary statistics

This section presents details on data and variables that we use to obtain preliminary results. The Climate Policy Uncertainty (CPU) index by Gavriilidis (2021) is based on newspaper coverage frequency, similar to the Economic Policy Uncertainty index by Baker, Bloom, and Davis (2016). Specifically, Gavriilidis (2021) searched eight US newspapers, including Boston Globe, Chicago Tribute, Los Angeles Times, Miami Herald, New York Times, Tampa Bay Times, USA Today and the Wall Street Journal, for certain terms. These are “uncertainty” or “uncertain” and “carbon dioxide” or “climate” or “climate risk” or “greenhouse gas emissions” or “greenhouse” or “CO2” or “emissions” or “global warming” or “climate change” or “green energy” or “renewable energy” or “environmental” and “regulation” or “legislation” or “White House” or “Congress” or “EPA” or “law” or “policy” with variants. The number of articles with relevant keywords is scaled by the total number of articles in each month. The index as a monthly time series from January 2000 to August 2022 is available on Baker, Bloom, and Davis’s website.

To identify sample selection criteria, we have an overview of climate policies in the U.S. and draw several conclusions. First, climate policies in the US primarily regulate energy, transportation, and industrial sectors. Second, prominent policies count the Clean Air Act, Clean Power Plan, Fuel Economy Standards, Renewable Fuel Standard, Energy Efficiency Resource Standards, Greenhouse Gas Reporting Program, etc. For instance, the energy sector is regulated by policies such as the Clean Air Act, which set emissions limits for power plants, and the Clean Power Plan, which set emission reduction targets for individual states based on their energy mix. Third, each policy and regulation has its own criteria for the firms or facilities that it regulates. However, some general criteria include emission threshold, facility type, industry sector, location, size or capacity, activity or process.

Given the various scopes of implementation of climate policies, we decided to choose publicly listed firms with geographical area in the U.S. These are firms that might be listed elsewhere but have their main operations, factories, facilities, etc. located within the U.S. territory and thus, are subjected to the U.S. climate policies. Given our broad interest in firms’ reaction to climate policy uncertainty, we select firms in any sector as large sample and firms in Energy, Industrials, Materials, Real Estate, and Utilities as a subsample. Using S&P Capital IQ Pro database, we obtain a sample of 8,867 firms. For these firms, we search in Eikon Refinitiv database for their reported Environmental Investment Expenditures, which is a unique variable only provided by Eikon Refinitiv. By far, other ESG data providers give environmental-performance measures like ratings, scores, and emissions but not environmental spending. However, it is noteworthy that this amount of investments and expenditures are self-reported and thus, subject to measurement errors.

We collect two more variables as controls for firm-specific environmental features: the estimated CO_2 and CO_2 equivalent emissions (in tonnes), and the Environmental Pillar Score provided by Refinitiv. To control for firms' financial performance, we follow Brown, Martinsson, and Thomann (2022) and collect the following variables from S&P Capital IQ: Cash-flow-to-assets, Sales-growth, Cash-holdings-to-assets, Total debt-to-assets. Since firms make environmental investments and expenditures on a yearly basis, we use an annual sample from 2000 to 2021. Most firm-level data are available yearly. The yearly average CPU index is shown in Figure 1. Firms who do not report environmental investment expenditures at all are dropped out of the sample. Tables 1 and 2 report detailed descriptions and summary statistics of all variables.

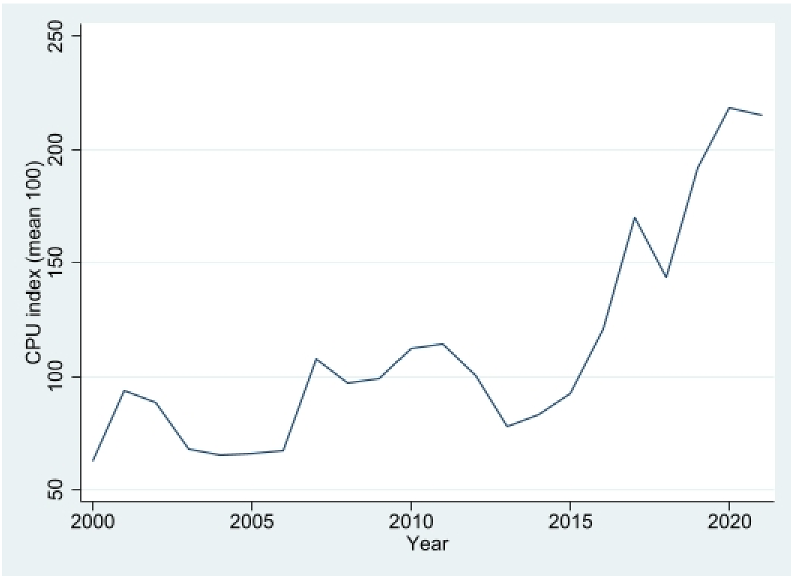

Figure 1: Climate policy uncertainty index from 2000 to 2021

Table 1: CPU and Environmental Investment Expenditures - all sectors

Variable name	Definition	Source
CPU_t	Climate Policy Uncertainty index based on U.S. newspaper coverage frequency. The series is normalized to have mean 100 from January 2000 to August 2022.	Gavriilidis (2021); Baker, Bloom, and Davis (2016)
$\ln(EE)_{i,t}$	The natural logarithm of all environmental investment and expenditures for environmental protection or to prevent, reduce, control environmental aspects, impacts, and hazards, including disposal, treatment, sanitation, and clean-up expenditure (in dollars)	Eikon Refinitiv
$ln(emis)_{i,t}$	The natural logarithm of estimated total CO_2 and CO_2 equivalent emissions (in tonnes). The total includes direct and indirect emissions (scope 1 and 2 according to the GHG Protocol).	Eikon Refinitiv
$score_{i,t}$	The Environment Pillar Score is the weighted average relative rating of a company based on the reported environmental information and the resulting three environmental category scores. Value ranges between 0 and 100.	Eikon Refinitiv
Sales growth$_{i,t}$	First difference in the natural logarithm of revenue (winsorized at the 1% and 99% level)	S&P Capital IQ
Cash-flow to assets$_{i,t}$	Cash flow (Net Income) divided by Total Assets (winsorized at the 1% and 99% level)	S&P Capital IQ
Cash holdings to assets$_{i,t}$	Cash and cash equivalents divided by Total Assets (winsorized at the 1% and 99% level)	S&P Capital IQ
Total debt to assets$_{i,t}$	Total debt divided by Total Assets (winsorized at the 1% and 99% level)	S&P Capital IQ

Table 2: Summary statistics - whole sample

	Obs.	Mean	Median	SD
CPU_t	71456	111.61	98.13	46.41
$\ln(EE)_{i,t}$	2291	16.87	17.14	2.39
$ln(emis)_{i,t}$	24854	10.64	10.67	3.00
$score_{i,t}$	25056	23.92	15.25	26.57
Sales growth$_{i,t}$	74279	.02	.01	.09
Cash-flow to assets$_{i,t}$	89033	-2.44	.01	13.34
Cash holdings to assets$_{i,t}$	92001	.18	.08	.25
Total debt to assets$_{i,t}$	93443	1.25	.18	6.15

5 Methods

In extracting causal effects of climate policy uncertainty on environmental-related investments, an ideal experiment would be having two groups of firms living in two separate environments, one with high climate policy uncertainty, the other with climate policy certainty. When a similar regulation is passed and implemented in both, the difference in investment between the two groups would be ascribed to climate policy uncertainty only. In reality, this experiment would best be approximated with a quasi-experiment such as the implementation of climate regulations. The second best option would be to simply regressing environmental investments on the news-based index as done in the literature.

In this research proposal, we start with the second best approach: estimating panel data models to observe how firms react to climate policy uncertainty over time. An issue is that not all firms have environmental initiatives and that they only report the amount of spending if they do spend it. This implies that climate policy uncertainty might not just impact how much a company invests in environmental matters but also whether a company invests at all. Hence, the correct specification shall include a sample selection equation within panel data models, for instance, the methods proposed by Kyriazidou (1997).

In this research proposal, we start with examining the effects of CPU on the variation in Environmental Investment Expenditures. We estimate a panel data model with unobserved heterogeneity as follows:

$$\ln(EE)_{i,t} = \lambda_t + \beta_1 CPU_t + \beta_2 \ln(emis)_{i,t} + \beta_3 score_{i,t} + \eta_i + \eta_t + C_i + U_{i,t} \quad (3)$$

where $\ln(EE)_{i,t}$ is the amount of environmental investment expenditures (in dollars) of firm i in year t, CPU_t is climate policy uncertainty index in year t (normalized to have mean 100 over the whole sample period), $score_{i,t}$ is the Environmental Pillar score between 0 and 100 for firm i in year t. η_i are firm-level financial performance controls. η_t are dummies for year fixed effects. C_i is unobserved heterogeneity or fixed effects.

Note that we have selected the amount of Environmental Investment Expenditures as an empirical proxy for firms' investment decision instead of a dummy indicator for having any investment even though this is readily available in Eikon Refinitiv. This is because panel data models are not good at predicting a binary outcome variable which would be best predicted using other models, e.g. a logit model. Given the prediction in section 3 above, the coefficient β_1 is expected to be negative, i.e. when it is uncertain whether a climate policy will be implemented (higher CPU or, in theoretical terms, lower probability of an emissions cap μ), companies are expected to invest less in environmental issues, assuming that climate policies captured in the news are about imposing an emissions cap.

Apart from controlling for year fixed effects and firm-specific financial performance, we control for firm-level environmental performance. When facing the possibility of being regulated in the future with regards to emissions, which is a usual criterion used in climate policies to include a firm, firms with higher emissions are more likely to take actions and invest or spend in environmental matters. Even though this is not explicitly modelled in Biais & Landier (2022), it is clear in the assumption that period-1 emission is higher than period-2 emissions given that the firm does invest in green technologies. Apart from emissions, we also control for third party's evaluation of a company's environmental performance through the score variable.

Equation (3) is first estimated using within transformation, first-differencing and random effects. Corresponding tests for strict exogeneity and for the conditional random effects hypothesis are also implemented. Even though the generalized methods of moments (GMM) would be the best estimation procedure, it appears that for the data at hand, GMM procedures using the no-contemporaneous-correlation and the general moment conditions do not converge and hence will not be reported.

6 Preliminary results

Table 1 displays results for the all-sector sample with and without firm-level financial-performance controls. Note that for this sample, Hausman specification tests show that Random Effects coefficients are not efficient nor consistent and thus, are not reported. Column 1 and 2 display within-transformation and first-differencing estimates without financial controls. Columns 3 and 4 display those with financial controls. While emissions and environmental score are significant in predicting the amount of Environmental Investment Expenditures, CPU is not. This is also true for the selected sectors. The number of observations with non-missing values for all variables is not so different between the all-sector sample and the selected-sector sample. This indicates that firms in the Energy, Industrials, Real Estate, Materials and Utilities sectors are more likely to report on their financial data and to have environmental initiatives.

However, these results are unreliable. The data panel is highly unbalanced and contains many missing values or zeros. Observations with zeros in Environmental Investment Expenditures and in emissions are thus undefined when log transformation is applied. Second, it is possible that CPU influences the likelihood of a firm to invest or not in environmental issues.

Table 3: CPU and Environmental Investment Expenditures - all sectors

	FE	FD	FE	FD
CPU_t	-0.01	0.00	-0.01	-0.00
	(0.03)	(0.00)	(0.03)	(0.00)
$ln(emis)_{i,t}$	0.19***	0.09*	0.19***	0.08
	(0.03)	(0.05)	(0.05)	(0.05)
$score_{i,t}$	0.01***	0.00	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	14.84***		16.21**	
	(5.66)		(7.15)	
N	2290	2019	1056	882
Year effects	Yes	Yes	Yes	Yes
Financial controls	No	No	Yes	Yes

Dependent variable is $ln(EE)_{i,t}$. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. FE: Fixed Effects (within transformation), FD: First Differencing. Financial controls include Sales growth, Cash-flow to assets, Cash holdings to assets, and Total debt to assets.

Table 4: CPU and Environmental Investment Expenditures - selected sectors

	FE	FD	FE	FD
CPU_t	0.01	-0.00	-0.00	-0.00
	(0.03)	(0.00)	(0.04)	(0.00)
$ln(emis)_{i,t}$	0.22***	0.10*	0.20***	0.09*
	(0.04)	(0.06)	(0.05)	(0.05)
$score_{i,t}$	0.01***	-0.00	0.01***	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Constant	12.03*		14.70*	
	(6.44)		(8.32)	
N	1736	1547	865	739
Year effects	Yes	Yes	Yes	Yes
Financial controls	No	No	Yes	Yes

Dependent variable is $ln(EE)_{i,t}$. Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. FE: Fixed Effects (within transformation), FD: First Differencing. Financial controls include Sales growth, Cash-flow to assets, Cash holdings to assets, and Total debt to assets. Selected sectors are Energy, Industrials, Real Estate, Materials, and Utilities, according to S&P Capital IQ/ GICS classification.

7 Future plan

The future plan for this research project includes several steps. The first is to tackle existing issues that comes with the panel regression methods. For instance, using the inverse hyperbolic sine transformation as in Colmer, Martin, Muuls, and Wagner (2020) helps deal with zero values better than the log transformation while preserving the interpretability of estimates. A second step is to investigate whether CPU influences the probability that a company invests in environmental initiatives. This is possible by estimating a Heckman (1979) type sample selection equation and then use the estimated likelihood as a regressor in the panel data model (Kyriazidou, 1997). However, such estimation method relies on the assumption that unobserved heterogeneity is exogenous, which is not true in the data.

A second step is to try a different identification strategy such as the difference-in-differences approach to extract the effects of a climate policy implementation on how firms behave. This approach requires identifying a major climate policy's entry into force and identifying two types of firms that are more or less similar but one is subject to the regulation while the other is not. The two types must be similar enough so that the treatment assignment is as close to random as possible. Within this approach, one way to identify the effects of climate policy uncertainty would be to compare firms' reaction to two climate policies: one which successfully passes with 51% votes for and 49% votes against, and one which fails with 49% votes for and 51% votes against. This search is plausible given publicly available data on the U.S. Congress and the European Parliament's votes on environmental issues.

A third step is to better identify whether and how much does a company invests in green technologies, either in R&D efforts for new technologies or in technology adoptive capacity. By far, the variable used for this purpose is a self-reported one provided Refinitiv. Another way to verify is to scan through companies' news and public communications and through R&D spending reported in their income statements.

A fourth step would be to analyze the EU sample given its special and long-operating Emission Trading Scheme. The number of free allocations of permits as well as the trading mechanism are likely to have implications on regulated firms' behaviour. Also, the government's theoretical decision to cap emissions could be empirically estimated by the total number of emissions permits issued at the beginning of each ETS phase. The challenges in studying the EU sample are in collecting firm-level environmental-related data prior to 2005, the first year in force of the ETS, and in slecting firms with similar characteristics . Transaction-level and installation-level data are, nonetheless, available on the European Union Transantion Log website.

8 Feedback and our response

Our original idea was to develop a theoretical model about impacts of sustainable investing on firms' investment decisions under uncertainty and to test it empirically. We wanted to develop a theoretical model in which an ambiguity-averse firm decides to invest in either a brown technology or a green technology. The brown one provides a certain profits stream but has high emissions while the green one has uncertain profits but low emissions. The firm's decision to invest in one of the two depends on their level of ambiguity aversion, their evaluation of the technology, and pressures from their shareholders and investors. The firm uses a real options pricing model to determine the price of the project and to know when is the best time to invest. Uncertainty of the green technology's profitability comes from uncertainty in the paths of climate change.

We presented this idea in class and received comments from Professor Steri. The general comment we received was to narrow down the scope to either a theoretical or an empirical work. Other suggestions are as follows. One, it is better to model risk aversion rather than ambiguity aversion. We can also let the firms and investors be risk-neutral to simplify the model. Second, it is suggested to do either a theoretical model or an empirical work, not both. Third, uncertainty can come from climate policies itself rather than from climate change. Or, we can also model climate change as a long-run disaster in the model.

After the presentation, we brought our modelling idea to get feedback from Professor Benteng Zou from the Department of Economics and Management. First, he commented that the real options model which relies on martingale will ignore the risk aversion feature that can lead to financial crisis. Second, he suggested us to take existing models, add in stochastic terms for uncertainty and then solve it with backward differential equations. However, we decided afterwards to focus on the empirical work.

On the empirical idea, we approached Professor François Koulischer who suggested us to keep in mind relevant theories which would help us identify causality instead of simply measuring correlation. Thus, we chose to start with the theoretical model of Biais and Landier (2022) to obtain empirical predictions.

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