SCHOOL OF
ECONOMICS AND
MANAGEMENT
LUND
UNIVERSITY

The Impact of Climate Policy Uncertainty on Firm Behaviour and Economic Performance: Case of UK

Master Thesis in Finance

Ea Dumancic

Master Essay I (NEKN02)
Department of Economics
Supervisor: Andreas Johansson

Abstract

We use a novel Climate Policy Uncertainty index to examine the spillover effects of US climate policy uncertainty on the profitability and investments of UK firms. Our static panel data model, incorporating firm and sector fixed effects, addresses endogeneity and unobserved confounders. The findings indicate that climate policy uncertainty negatively impacts firm investments. We additionally explore if the effects are influenced by CO2 emission levels and if high ESG scores can mitigate these adverse effects. This thesis contributes to climate uncertainty literature, suggesting that investments in climate social responsibility can reduce uncertainty's negative impacts.

Keywords: Climate Policy Uncertainty, firm-level data, fixed effects, UK

Table of Contents

List of Tables

List of Figures

Introduction

Climate change stands as one of the most pressing challenges of the 21st century, as its effects are felt across ecological, social, and economic realms. Scientific consensus attributes climate change to the emission of greenhouse gases stemming from human activity, primarily burning of fossil fuels and deforestation (IPCC, 2014). Consequences can be seen across the globe, from rising sea levels, frequent and extreme weather events, to increase in global temperature (IPCC, 2018). Policymakers worldwide are faced with a mounting challenge of constructing and implementing policies that will tackle both the causes and the effects of climate change. The International Monetary Fund highlights that stringent climate policies in major economies like the US can influence trade, financial markets, and shared environmental resources, with spillover effects of these policies noticeable across the globe (Zhao, 2024). An example of that is the Inflation Reduction Act, a climate policy the US passed in August of 2022, which caused concerns in the United Kingdom regarding its impact on businesses (Hakim, 2023). This uncertainty brought upon by a climate policy stems from the ambiguity regarding future regulatory environment encompassing emission standards, recycling rules, and carbon taxes, and it presents a problem for companies. Considering that nowadays climate policies affect investment decisions, production processes, market competitiveness, and much more, firms cannot ignore the impact of uncertainty around current and future climate policies when it comes to their business decisions. This leads us to pose a question: does US climate policy uncertainty affect firm operations in the United Kingdom?

In this thesis we aim to investigate this question, specifically, whether spillovers from US's climate policy uncertainty affect firms in the UK and their planned investments, research and development expenditure (R&D), as well as return-on-assets (ROA) and return-on-equity (ROE). Similar question has already been posed in the context of US firms, however our focus on the effect of spillovers serves both as a novel research question and as a way of eliminating unwanted endogeneity from our analysis, as firms in the UK cannot affect climate policies in the US. The Climate Policy Uncertainty index (CPU), a recently developed index by Gavriilidis (2021), is used as our proxy for US climate-related policy uncertainty. Furthermore, we expand our analysis to whether firms with higher CO2 emissions are more prone to detrimental effects of climate policy uncertainty, and if it's possible to mitigate said effects by greater engagement in climate social responsibility (CSR), proxied by a company's ESG score.

For the purpose of this analysis we employ static and dynamic panel data models on UK firm-level data spanning last twenty years, with an addition of firm, sector, and time fixed effects to control for any unobserved time-invariant confounders. Our main findings imply that Climate Policy Uncertainty index decreases firm's short-term investments, as well as their investments into fixed capital, and return-on-assets. Our results are in line with previous literature that suggests firms postpone their investment when climate policy uncertainty is high (Ilyas et al., 2022; Ren et al., 2022a). Furthermore, second part of our analysis shows that ESG is able to mediate adverse effects of climate policy uncertainty, implying that firms may invest into CSR to boost their financial performance and long-term sustainability, a notion discussed by Vural-Yavaş (2021) and Azimli (2023).

This thesis therefore contributes to the literature by expanding the area of research into policy uncertainty by examining the role of climate policy uncertainty on firm-value relationship. Spillovers of climate-related policy uncertainty originating in the US have not yet been evaluated in the context of firms in the UK, particularly whether firm specific factors such as CO2 emissions and ESG scores amplify uncertainty effects. Additionally, we address the mediating effects of firm's climate social responsibility engagement on uncertainty as an important guideline to future business decisions.

1.1. Previous literature

Economists tend to describe uncertainty as "unpredictability of fiscal, regulatory, and monetary politics" (Al-Thaqeb & Algharabali, 2019) and in a broader sense it is inability to accurately predict future events and their likelihood of happening (Frank H. Knight, 1921). A 1983's study by Bernanke showed that uncertainty is one of the causes of employment cuts and shrinking investments, introducing uncertainty as a topic of interest in economic studies. The field is expanded by Bloom (2009), who posits that uncertainty reduces economic growth and therefore impacts the economy as a whole. Economic uncertainty in particular is defined as any unexpected change that can affect the macroeconomic environment, including but not limited to government policies, fiscal decisions, monetary changes, etc. (Abel, 1983). Policy uncertainty, however, pertains to ambiguity about future government decisions and regulatory framework that affects spending and investing decisions of businesses and individuals via increased risk (Al-Thaqeb & Algharabali, 2019). Uncertainty is best observed in times of crisis, as during 2008's Global Financial Crisis policymakers were themselves unsure of the future state of the economy and delayed decisions on future tax rates, monetary policies, and government spending (Baker et al., 2016). This, according to the authors, lead to slow rates of recovery after the crisis, as the uncertainty stalled investor decisions.

Despite uncertainty's effects being observable, the challenge is how to measure it. Several proxies for uncertainty were developed during the years with a goal of monitoring it, with one of the oldest measures being the VIX index of the Chicago Board Options Exchange[1]. Volatility Index, or VIX, measures the standard deviation of stock prices and stock returns and has been used as a key proxy for market risk in financial studies on stock returns, volatility risk premium, and derivatives (González-Marrón et al., 2020). However, its limitation is that it is purely a US-centric measure of market based uncertainty, hence its limited use outside of the US market. Another uncertainty index was developed by Jurado et al. (2015) who employ data from 132 macro indicators of US economy in order to construct a measure of macroeconomic uncertainty. Da et al. (2015) on the other hand measure investor sentiments and fears via text-based web search and use it as a base of their FEARS[2] index. The authors suceessfully use it to predict temporary increases in volatility and mutual fund flows (Da et al., 2015). Common issue with uncertainy indices, however, are lack of public-availability, difficulty expanding them across longer time periods, and being US-centric and thus not applicable to other countries (Al-Thaqeb & Algharabali, 2019).

Lack of a good uncertainty measure lead to the development of the most popular and widely used uncertainty proxy nowadays: the Economic Policy Uncertainty (EPU) index. Baker et al. (2016) utilize news coverage to quantify overall volume of articles across ten leading US newspapers that contain at least three keywords related to 'uncertainty', 'economy', 'congress', 'legislation', 'Federal Reserve', and more. This volume of articles is then scaled by total number of articles by each newspaper and month, standardized, and lastly averaged to a single value that represents the EPU index. The index spikes in value around crises (the 2008 Global Financial Crisis), wars (Gulf Wars), debt-ceiling disputes in the US as well as presidential elections. Nowadays there exist Economic Policy Uncertainty index values for more than 25 countries, all calculated following the same procedure (Al-Thaqeb & Algharabali, 2019; Baker et al., 2016). Since its inception, EPU was predominantly used in market-based research to examine effects of uncertainty on stock volatility (Liu & Zhang, 2015; Yu & Huang, 2021) and stock market returns (Christou et al., 2017; Guo et al., 2018; Xu et al., 2021). Gholipour (2019)

---

[1] https://www.cboe.com/tradable_products/vix/
[2] FEARS index stands for Financial and Economic Attitudes Revealed by Search (Da, 2013).

uses panel vector autoregression to show that real estate activities, financial market activities, and patent applications react negatively to increased EPU in the short-run. Applying a similar VAR framweork, Trung (2019) posits that spillovers of US policy uncertainty happen in one to four months after the initial shock and affect real output of global economies. The work of Biljanovska et al. (2021) supports these findings, adding that EPU shocks originating in the US mostly reduce private consumption growth in Europe and China. Cho et al. (2023) explore the extent of EPU spillovers even further, revealing that US and Europe are transmitters of uncertainty shocks, whereas countries such as China, Japan, and Korea are the recipients.

Economic Policy Uncertainty index has also been used in assessing uncertainty's effects on corporate decisions. Gulen & Ion (2016) argue that EPU negatively impacts corporate capital investment, and the effect is amplified for firms comitting to long-term irreversible investments, as well as for firms that are primarily government contractors. This adverse effect of EPU on investments is further confirmed by Farooq et al. (2022) and Zhang et al. (2015). Additionally, heightened EPU has a negative impact on the firm's cost of financing (Jens, 2017; Zhang et al., 2015) but increases the amount of company's cash holdings (Im et al., 2017).

Examining EPU's effects on various firm and country level variables is of importance for future predictions about uncertainty effects, yet efforts should also be placed on investigating what could help mitigate the influence of uncertainties. Ali et al. (2023) touch upon that topic in their research on the relationship between EPU and financial stability. They find that negative effects of EPU can be mitigated by good governance, with the effect varying between banks, regions, and market structures. A study by Zhang et al. (2024) on the other hand investigates the role of the firm's ESG score in the relationship between EPU and corporate investment. ESG score refers to company's performance on a variety of sustainability issues in three categories: environmental, social, and governance. It has increasingly been used as an indicator of company's investment into social and environmental responsibility, hence why investors nowadays perceive firms with a high ESG score as more attractive to invest into and more resilient to market fluctuations (Dkhili, 2023). By employing a dynamic GMM model on 13 years of data on BRICS firms, Zhang et al. (2024) confirm that EPU has a negative impact on corporate investment, but add that firms with high ESG score were less prone to delaying investments. The authors suspect that ESG mitigates EPU through raising firm's reputation and thus reducing investing costs, as well as improving company's risk management. In contrast to negative effect of EPU on firm investments, Ilyas et al. (2022) and Vural-Yavaş (2021) find that firms do increase their investment in ESG and sustainability-related activities in response to high EPU.

Because the process of EPU's construction is publicly available and relatively straightforward, it is easy for researchers to implement it on another country's data, or even on a global scale, as in the case of the Geopolitical Risk[3] Index. Gavriilidis (2021) applied this methodology on uncertainty related to climate policies, constructing a novel index of Climate Policy Uncertainty.

The CPU index serves as a proxy for climate policy uncertainty in our study and captures uncertainty related to US climate policies, such as Donald Trump announcing US withdrawal from the Paris Accord in June of 2017, or 2023's Environmental Protection Agency's announcement of new multi-pollutant emission standards. To construct CPU, Gavriilidis (2021) counts how many articles have included keywords related to 'climate', 'greenhouse gas', 'uncertainty', and 'climate risk' across eight major newspapers in the US on a monthly basis[4]. The volume of articles containing these keywords is scaled by the total number of articles published in each of the eight newspapers every month, then standardized and averaged across all newspapers (Gavriilidis, 2021). Contrary to the climate change index by Engle et al. (2019), it discards articles discussing physical consequences of climate change, such as floods, fires, extreme weather events, etc. The final product, the CPU index, interprets an increase in frequency of articles discussing selected keywords as an increase in climate policy uncertainty. In essence, if the uncertainty is of such extent that newspapers report on it with heightened interest, the index will pick it up and reflect that uncertainty with its increased value. For example, in 2020 Donald Trump rejected stricter air quality standards proposed by EPA, causing CPU to skyrocket in value. The increase in the index signified that the uncertainty about US's future climate policies was high, not only because EPA's policy making proposals were rejected by the Trump Administration, but because this decision could again be reversed in Congress, depending on the results of upcoming US elections (Lavelle, 2020). This volatility in implementing climate policies is what presents a problem for firms that have to organise their business operations, and is the basis of our research question.

Gavriilidis (2021) and Guesmi et al. (2023) use the index to investigate the relationship between climate policy uncertainty and CO2 emissions, whereas a myriad of other articles try to quantify the effects of CPU on stock returns or stock volatility in the US (Lasisi et al., 2022; Mahjoubi & Henchiri, 2023; Raza et al., 2024; Xu, 2017), China (Chen et al., 2023; Lv & Li,

---

[3] Available on www.policyuncertainty.com and constructed by Dario Caldara and Matteo Iacoviello, GP index counts the number of articles covering geopolitical tensions.

[4] Other keywords that CPU is picking up are 'legislation', 'regulation', 'emissions', 'global warming', 'renewable energy', 'Congress', and its variants.

2023) and Europe (Tedeschi et al., 2024). Less attention has been dedicated to assessing the effects of CPU on firm-level variables, however Persakis (2023) investigates effect of CPU on US Fortune 1000 firms. Employing OLS and fixed effects, he presents empirical results of CPU positively affecting ESG performance but negatively affecting firm performance proxied by ROE. Adverse effects of climate policy uncertainty on firm value are more dire for firms with more fixed assets, as presented by Ongsakul et al. (2023) and Berestycki et al. (2022), but less evident for firms that pay higher dividends, a result that is echoed by Ayed et al. (2024), who find that firms pay higher dividends in periods of heightened climate policy uncertainty. CPU's effect on other firm-level variables is investigated by Ren et al. (2022) who choose as their outcome variable firm-level total factor productivity (TFP) and find that CPU reduces TFP of Chinese firms. Niu et al. (2023) find that CPU has a detrimental effect on green technology innovation of a sample of Chinese companies, whereas Huang & Sun (2023) give evidence that the effect of climate policy uncertainty on firm investment in China can last up to three quarters. The effects are more pronounced for state-owned and carbon-intensive enterprises. Similarly to our study, Azimli (2023) analyses CPU's effects on climate social responsbility engagement of firms using fixed effects in a panel setup, finding positive relationship between the two.

Overall, previous research on uncertainty indices presents mostly uniform results, where uncertainty is seldom good for firms and the economy as a whole. Studies on CPU suggest that it has negative effects on firm-level variables, but also that there are spillover effects of US's climate policy uncertainty to economies worldwide. However, the literature on CPU's effects is still relatively new and we believe that the index could be used for further resarch on the effects of climate-related policy uncertainty on firms, households, and markets alike. It is, however, important to note its limitations, and address important caveats that were overlooked by earlier literature on the subject. The lack of effective control variables, such as macroeconomic variables, and EPU, can result in the omitted variable bias in the results, and are an issue in the studies done by Azimli (2023), Berestycki et al. (2022) and Persakis (2023). Choice of models in these studies often incorporates only static panel data models, whereas dynamic models could prove to be a better fit if firm-level data are used, mainly because of issues with biased OLS and fixed effects models (Iqbal et al., 2020).

This study aims to account for highlighted limitations and expand the area of research further. Through the construction of our research question and use of both fixed effects model and the GMM estimation, we attempt to improve on past studies and take a closer look at CPU's cross-country effects on firm decisions. We hypothesize that CPU has a negative effect on firm-level values, particularly investments, as that has so far been posited by the literature on the topic. Furthermore, previous studies have found mitigating effects of ESG when it comes to effects of Economic Policy Uncertainty index, hence we hypothesize that such a claim will hold against CPU as well. Additionally, we suspect that the firms with higher CO2 emission levels are more exposed to CPU's adverse effects, as uncertainty about future climate regulations and laws are more detrimental to high-emitting firms (Carattini & Basaglia, 2022).

Data

3.1. Climate Policy and Economic Policy Uncertainty Index

The Climate Policy Uncertainty index was obtained from policy uncertainty website[5] maintained by Baker, Bloom, and Davis. Our sample consists of monthly values from 1998 to 2023 that we transform into annual values by calculating their 12-month average. This is done to match the granularity of accounting data which is only published once per year.

Since the CPU index pertains only to uncertainty related to climate policies, to be able to properly capture its effects on firm's behaviour we need to control for uncertainty stemming from non-climate related economic policies. Hence, in our analysis we follow the work of Carattini & Basaglia (2022) and include EPU index for the UK with an aim to control for any uncertainty relating to UK's economic policies.

As previously mentioned, the main assumption of this thesis is that climate policy uncertainty originating in the US affects behaviour of firms in the UK. If that is indeed the case then US's economic policy uncertainty affects firms in the UK just the same. Such notion has been supported in previous literature concerning CPU and EPU, and we additionally consult articles by Biljanovska et al. (2021) and Clausen et al. (2019) to support this assumption, as both have found significant spillovers of US economic policy uncertainty to not only UK but other global economies. Thus, it is important to bear in mind that UK's economy is affected not only by internal economic policy uncertainty but external as well, mainly the one stemming from the US. This motivates our inclusion of US' EPU index. Having both indices in our regressions should therefore sufficiently control for UK's macroeconomic environment, as well as any policy uncertainty spillovers stemming from the US. Figure 1 provides a comparison between UK's and US's Economic Policy Uncertainty index.

[5] www.policyuncertainty.com

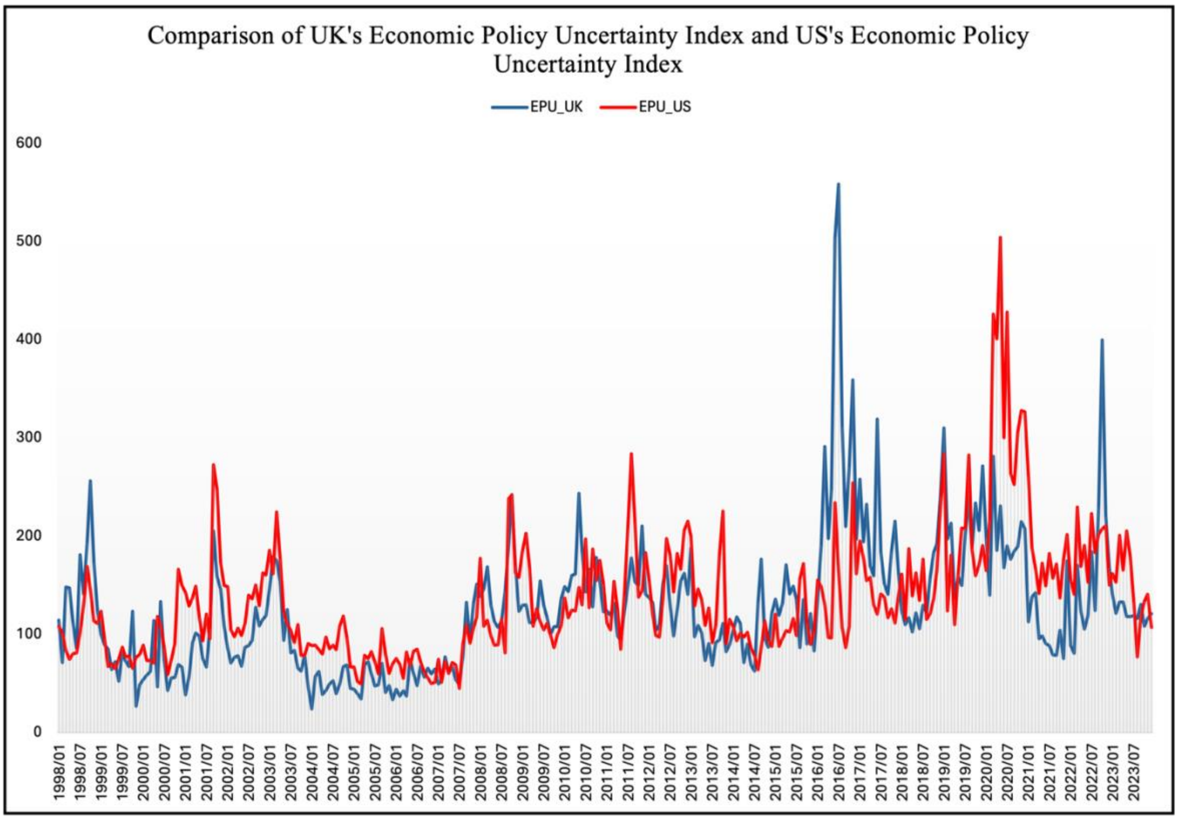

Figure 1: Comparison of Economic Policy Uncertainty index of UK and US

Peaks in uncertainty corresponding to the 2008 financial crisis, as well as the COVID-19 pandemic, are captured by both indices. However, certain policy uncertainties are unique to each country, with the most obvious example being UK's EPU peaking in 2016 at the time of the Brexit vote, whereas US's EPU exhibits no high values at that time.

The next question we need to consider is whether CPU can properly isolate uncertainty related to climate policies. First we compare the CPU index against EPU for both UK and US using a correlation matrix presented in Table 1. Correlation coefficient of 0.7 indicates relatively strong correlation based on conventional measures across 24 years of data (Schober et al., 2018). This is not surprising as both indices are based on policy uncertainty of the US, and CPU most likely picks up general policy uncertainty (Berestycki et al., 2022), as well as any sort of uncertainty in climate policies that may originate through discussions of economic policy. Baker et al. (2016) found similar correlation coefficient between EPU and VIX and described this difference between the two values as an important source of differential variation. Relationship between CPU and EPU for UK exhibits moderate correlation, similarly to correlation between EPU indices of the two countries. Despite all of our indices being correlated, we are still lead to believe they capture different sources of uncertainty, affirming our choice of using them as controls in our models.

Table 1: Correlation matrix for Policy Uncertainty indices

Variable	CPU	EPU_US	EPU_UK
CPU	1		
EPU_US	0.73	1	
EPU_UK	0.53	0.61	1

Second, in Figure 2 we graphically compare CPU and US's EPU using monthly values for both. The two indices experience peaks in values at different times, with most notable divergence happening in 2020. During COVID-19 pandemic, EPU's value skyrocketed whereas CPU's value was low, suggesting that economic uncertainty was far greater during pandemic than the climate one, as it was more relevant at the time. Another example can be seen in year 2021 when CPU's values were far higher than EPU's, coinciding with the Trump's reversal of new EPA standards (Lavelle, 2020). Figure plotting CPU against UK's EPU follows the same pattern and can be found in the **Error! Reference source not found.**.

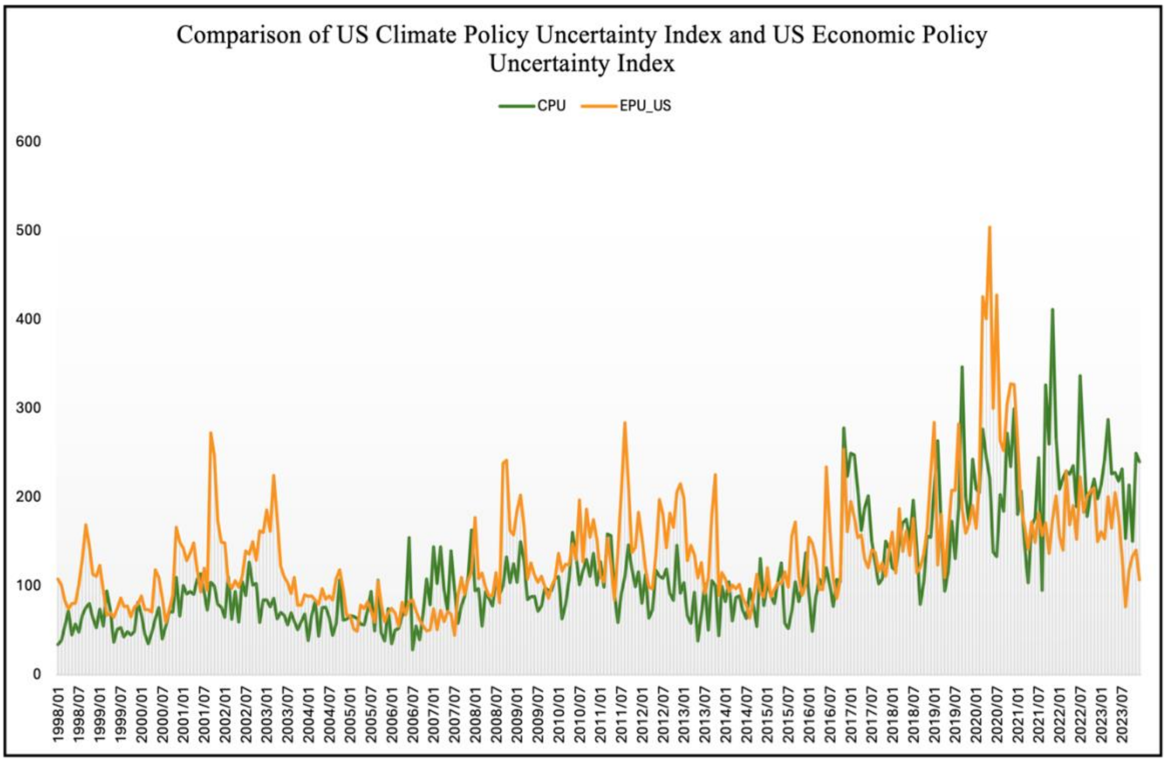

Figure 2: Comparison of Economic and Climate Policy Uncertainty index of the US

The evidence suggests that economic policy uncertainty inevitably affects the discussion of any climate policies, but EPU does not pick up climate policy uncertainty in the same extent as CPU is designed to do. Conversely, CPU does not seem to pick up uncertainty stemming from policies not related to climate. Combining the different nature of constructing each of these indices with our tests, we think it is sufficient to trust that CPU predominantly captures climate policy uncertainty that is overlooked by other uncertainty indices, allowing us to proceed with our main analysis.

3.2. Sample and Descriptive Statistics

Data needed for the purpose of this thesis are firm-level data, specifically, accounting data for public firms based in the UK that are published once per year. We obtain it from the Thomson Reuters Refinitiv[6] database for the period from 1999 to 2023. Main variables of interest are short-term investments, long-term investments, R&D expenditures, Return-on-Equity, and Return-on-Assets. These variables have been used in previouos literature on this subject and should provide a representative state of firm's financial health (Berestycki et al., 2022; Iqbal et al., 2020; Persakis, 2023). Four out of seven variables are directly tied to investments, as we are interested in gauging whether uncertainty increases or decreases firm-level investments. On top of looking at short- and long-term investments, we include R&D expenditures and construct the firm investments variable. Firm investments, also used by Berestycki et al. (2022) and Sorbe & Johansson (2017) is calculated as:

$$FI_t = FixedAssets_t - FixedAssets_{t-1} + Depreciation_t + Amortization_t$$

By netting for depreciation and amortization, this measure isolates the value of new fixed assets acquired by the firm in year *t* (Berestycki et al., 2022). The intuition is that fixed assets are typically irreversible compared to other types of firm capital, hence firms with greater share of fixed assets may be more prone to CPU's negative effects (Carattini & Basaglia, 2022). For evaluating firm performance we employ two profitability ratios as proxies: ROA and ROE. Return on equity is defined as firm's net income divided by firm's total equity, and it is one of the most employed ratios in previous research for evaluating firm performance (Nguyen & Trinh, 2023; Persakis, 2023). Return on assets is calculated as net income divided by the average of total assets, hence it evaluates how much profit a company can generate from its assets (Iqbal et al., 2020), and is often used as a measure of management quality and liquidity risk. Both ratios give us information on firm profitability.

Furthermore, we discard firms that have less than five years of accounting data available, as proposed by Azimli (2023), leaving the final dataset at 1,498 firms. Since we have individual level data for a large number of firms across a 24-year time-series, the dataset in question

[6] https://eikon.refinitiv.com/

represents a panel dataset. Firms are also sorted into one of the 12 sectors, with most firms belonging to Technology sector, followed by Financial sector and Consumer Cyclicals sector.

Following Iqbal et al. (2020) and Azimli (2023) we control for firm size, which we proxy by log value of firm's Total assets. Sritharan (2015) also posits that firm size is positively related to firm's profitability, hence why we include it in the regression. Considering that accounting data are published once per year, our index values for CPU and EPU's are averaged to get annual values. Macroeconomic control variables of choice are UK's annual GDP rate and UK's yearly inflation rate, obtained from the World Bank Databank[7]. GDP growth rate and inflation rate serve as proxies for economic activity and monetary conditions, respectively (Phan et al., 2018; Yousefi & Yung, 2022). Combined with the EPU variables, we should be able to sufficiently control for the macroeconomic environment in which the firms operate (Carattini & Basaglia, 2022).

For sensitivity analysis we employ firm's ESG scores as well as their CO2 emissions. Data on these variables can also be found in Refinitiv's database, however the number of observations is considerably smaller since firms started to report these values in 2008 and 2003, respectively. Furthermore, not all firms disclose this data. Refinitiv's ESG specialists measure a company's relative ESG performance based on publicly-reported data on their Environmental, Social, and Governance practices, and the employed methodology can be found on LSEG website[8]. Data on CO2 emissions, on the other hand, are reported by firms themselves in millions of tonnes annually.

Previous literature on the subject recommends winsorizing accounting variables at 1% and 99% level, which we apply to our sample (Azimli, 2023; Iqbal et al., 2020). This in effect means that we compute the smallest 1% from all our observations and set them equal to the first smallest value greater than those 1% (Wilcox, 2003). Hence, instead of removing the smallest 1% (the biggest 1%), we reset them to first smallest (largest) value in the sample of observations. Winsorizing firm-specific variables serves to avoid the over-estimations of outliers (Iqbal et al., 2020; Persakis, 2023). Complete descriptive statistics for the sample in question is presented in Table 2.

[7] https://databank.worldbank.org/

[8] Environmental score consists of three categories: firm's resource usage, innovations, and emissions.
Social score measure firm's human right activities, workforce and community practices.
Governance score is evaluated through firm's management, shareholders, and CSR strategy. (Understanding ESG Data and Scores from Refinitiv | Issuer Services | LSEG, 2024).

Table 2: Descriptive statistics of the working sample

Variable	Mean	Standard Deviation	Min	Max	No. of Obs
Panel A: Summary statistics for dependent variables					
Short-term investments	151.71	707,96	0	13,211	5,667
Long-term investments	1954,7	18,784.6	0	548,154	14,845
R&D expenditures	124.95	568.72	0	8,069	2,800
ROA	-0.34	21.63	-2942.7	189.83	22,798
ROE	0.12	2.38	-76.51	172.5	9,262
Firm investments	80.12	1956.3	-178,044	126,665	33,024
Panel B: Summary statistics for control variables					
Total assets	8510.74	81,394	0	2,438,027	24,192
Cashflow	268.29	1445.74	0	50846.4	18,196
CPU	116.09	54.61	57.56	225.41	38,922
EPU_UK	126.65	54.04	49.65	289.14	38,922
EPU_US	136.01	50.82	67.14	326.32	38,922
GDP	1.94	2.01	1.55	2.27	37,425
GDP rate	1.71	3.26	-10.36	8.67	37,425
Inflation rate	2.42	1.71	0.37	7.92	37,425
ESG	47.58	19.77	1.02	95.58	5,864
CO2 emissions	1.741	8.51	0	112	4,589

Notes: Accounting variables and GDP are given in millions of pounds sterling. CO2 emissions are given in millions of tonnes. Sampling period for accounting variables is from January 1999 to December 2023, and January 1998 to December 2023 for all indices used. All accounting variables are winsorized at 1% and 99% level to reduce the impact of outliers on the results.

Empirical strategy

What is the effect of CPU on firm-level variables? seems like a straightforward research question. However, when designing an empirical model that can properly answer this we have to first be mindful of potential endogeneity problems. Endogeneity refers to the bias in our estimation caused by vector of explanatory covariates being correlated with the error term (Angrist & Pischke, 2009). Considering our research objective, endogeneity in our model can stem from primarily two sources: omitted variable bias and measurement errors. We consider the issue of reverse causality as a source of endogeneity that is not applicable in our case, as firm behaviour of UK companies cannot affect climate policy uncertainty captured in the US.

Omitted variable bias is caused by unobserved covariates that may jointly affect our dependent and independent variables, or in other words, if we suspect that our dependent variables depend on explanatory variables that are unobservable but correlated with the observed ones we are most likely dealing with the omitted variable problem (Angrist & Pischke, 2009). The consequence of not including all relevant variables in the model is bias in estimated coefficients. Another source of bias can be caused by measurement errors in our independent variables which causes downard bias in our estimates, again giving rise to endogeneity that interferes with our estimation and leads to loss of precision in estimates (Brooks, 2019). Because of endogeneity's inherent issue of not being testable, we must design an approach to our estimation that mitigates the bias caused by endogeneity, and for this we turn to the panel dataset.

Our panel dataset consists of *N* firm observations repeated over a span of *T* years. Because it involves a large number of cross-sectional units over a small number of time-series observations for each unit, we can take advantage of its panel nature to fix potential endogeneity issues (Roberts & Whited, 2012). Consider this model:

$$FV_{i,t} = \alpha + X'_{i,t}\beta + \upsilon_{i,t}, \qquad i = 1, \dots, N; t = 1, \dots, T \tag{1}$$

Here $FV_{i,t}$ is our firm-value variable, $X_{i,t}$ is a vector of exogenous regressors, and $\upsilon_{i,t}$ is the error term. Following Angrist & Pischke (2009) we separate the error term into two parts:

$$\upsilon_{i,t} = \eta_i + \varepsilon_{i,t}$$

Error term is therefore the sum of the part that varies over time, $\varepsilon_{i,t}$, and the part that does not vary over time, η_i. Factors that do not vary over time, i.e. are fixed, are unobserved individual factors, in our case unobserved firm-specific factors such as management skills, corporate culture, access to resources, and more (Jacobson, 1990). These firm characteristics may be correlated with independent variables in our model and consequently affect the dependent variable. By removing them from our model we are effectively controlling for these unobserved heterogeneities and ensuring that independent variables are not confounded by firm-specific factors (Brooks, 2019). Such is the premise of the within-estimator, where we subtract individual-specific values over time from the main model and thus eliminate these fixed effects. The estimation goal is to consistently and efficiently estimate our parameter of interest, CPU, and its yearly variations while accounting for the presence of unobserved time-varying confounders (Angrist & Pischke, 2009). Our model of choice is the following:

$$y_{i,t} = \beta_0 + \beta_1 CPU_{t-k} + \beta_2 X'_{i,t-k} + \delta_i + \delta_s + \varepsilon_{i,t} , \qquad k = \{0, 1, 2\} \tag{2}$$

We regress our main independent variable CPU_{t-k}, against $y_{i,t}$, one of our six outcome variables: short-term investments, long-term investments, firm investments, R&D expenditure, ROA, and ROE. Vector of controls, $X'_{i,t-k}$, consists of EPU index for UK and the US, firm size, UK's GDP rate and UK's inflation rate. In order to capture firm-specific factors we include firm fixed effects, δ_i, as well as sector fixed effects, δ_s, so as to absorb sector specific shocks. Finally, $\varepsilon_{i,t}$ is the idiosyncratic error term.

This specification is estimated without time fixed effects, as they are perfectly collinear with our EPU indices causing them to drop out of the regression. As stated by Azimli (2023) and Baker et al. (2016), time fixed effects absorb all the explanatory power of policy uncertainty indices. The model incorporating time fixed effects is therefore detailed in subchapter 4.2.

Berestycki et al. (2022) and Ongsakul et al. (2023) recommend that all accounting variables be lagged by at least one period considering financial reports are publicly available with a lag. This is why in the first specification of our model (2), we include CPU and EPU's lagged by one period. In our second specification we add additional two-year lag for our index values, as we assume that investment expenditures are often planned long-term by management. In both versions of our regressions the rest of our control variables are included at lags of *t* and *t-1*.

We run a Hausman test before each regression in order to confirm our fixed effects specification is indeed the best choice considering our model, and all the regressions pass the test at $p < 0.000$ (Angrist & Pischke, 2009). Correlation coefficients among the dependent variables are relatively low, hence we do not consider multicollinearity as an issue (Azimli, 2023; Berestycki et al., 2022). Upon visual inspection all of our variables suffer from heteroskedastic residuals which we further confirm by the Wald test resulting in $p>0.05$, meaning that the variance of the error term is not constant. Heteroskedasticity does not cause bias to our estimates but it does bias our standard errors (Brooks, 2019). In addition to taking a natural logarithm of our variables to correct their distribution (Brooks, 2019) we include standard errors clustered at the firm level as a way of correcting our standard errors (Stock & Watson, 2008) and accounting for potential error correlation across firms (Carattini and Basaglia, 2022).

4.1. Sensitivity analysis

In the second part of our analysis we consider what factors mitigate or exacerbate effects of CPU on firm-level variables. For that purpose we make use of interaction variables. In first specification, we take the log change of our CPU and EPU variables before interacting each one of them with our ESG variable (Azimli, 2023). The model is then constructed by regressing the log difference of each of our dependent variables on log change of our interaction variables, effectively estimating a first-differences model (Berestycki et al., 2022). Advantage of this model is twofold: it removes collinearity between time fixed effects and our uncertainty variables, allowing us to include time fixed effects in our model; and second, we further reduce concerns of omitted variable bias (Berestycki et al., 2022). Time fixed effects capture unobserved time-varying factors i.e. systematic variation in firm behaviour over time that is common to all entities in the panel (Angrist & Pischke, 2009). By being able to introduce time fixed effects into our specification we account for time-specific factors that may introduce bias back to our estimators in the form of omitted variable bias. Another reason for including time fixed effects is to control for any cyclical trends or patterns that occurred during our time period as it is assumed that these trends affected all firms in the panel simultaneously (Roberts & Whited, 2012). Thus, employing a two-way fixed effects enhances the validity and robustness of the analysis, allowing for more accurate conclusions about the impact of external factors on firm behavior over time. The model with the interaction variable of CPU and ESG is the following:

$$\begin{aligned}\Delta\log\left(y_{i,t}\right) = {} & \beta_1\Delta\log\left(CPU_{i,t-1}\right)\times\log(ESG_i) \\ & + \beta_1\Delta\log\left(EPU_{UK_{i,t-1}}\right)\times\log(ESG_i) \\ & + \beta_1\Delta\log\left(EPU_{US_{i,t-1}}\right)\times\log(ESG_i) + \beta_3 X'_{i,t-k} + \delta_i + \delta_s \\ & + \delta_t + \varepsilon_{i,t}\end{aligned} \tag{3}$$

The rationale of this model is that omitted variables cannot pose a problem unless they are mediated in proportion to the ESG, which should be highly unlikely. As in the main regression analysis, we include our control variables in years *t* and *t-1*, along with firm, sector, and time fixed effects. Next we assess whether high CO2 emissions cause firms to be more susceptible to CPU's adverse effects with the following model:

$$\begin{aligned}\Delta\, log\left(y_{i,t}\right) = {} & \beta_1 \Delta\, log\left(CPU_{i,t-1}\right) \times log(CO2_i) \\ & + \beta_1 \Delta\, log\left(EPU\_UK_{i,t-1}\right) \times log(CO2_i) \\ & + \beta_1 \Delta\, log\left(EPU\_US_{i,t-1}\right) \times log(CO2_i) + \beta_3 X'_{i,t-k} + \delta_i \\ & + \delta_s + \delta_t + \varepsilon_{i,t}\end{aligned} \tag{4}$$

Once again we take the log difference of our index variables and then interact the CO2 variable with CPU and EPU for US and UK. Our aim with including the interaction variable is to assess CPU's effects on the firm based on how exposed the average firm is to CO2 emissions. Additionally, by interacting our explanatory variable of interest with CO2 emissions we are again reducing the effect of omitted variables bias in our model (Berestycki et al., 2022). We keep control variables from the main analysis but include sector, firm, and year fixed effects. Results are given in Section 5.2.

4.2. Robustness check

As a robustness check we have decided to approach our main analysis using an alternative estimation method: the two-step-system Generalized Method of Moments (GMM) model of Blundell & Bond (1998). This supplemental approach has been employed by Ilyas et al. (2022) and Nguyen & Trinh (2023) as a way of controling for endogeneity concerns between firm variables and uncertainty indices. The inclusion of a lagged dependent variable as an additional regressor transforms our regression (2) into a dynamic model, as it supposes that the relationship between variables is dynamic. The model would then be as follows:

$$y_{i,t} = \beta_0 + \beta_1 y_{i,t-1} + \beta_2 CPU_{t-1} + \beta_3 X'_{i,t-k} + \eta_i + \varepsilon_{i,t} \tag{5}$$

This is our *Level* equation. As previously mentioned, η_i is the unobserved time-invariant heterogeneity while $\varepsilon_{i,t}$ is the idiosyncratic error of our model. We assume that the individual-specific effect is correlated with out $X'_{i,t-k}$ vector of covariates, which was the basis of our within estimation. The problem with this model is that the lagged dependent variable is correlated with the individual specific effect $E(\eta_i|y_{i,t-1}) \neq 0$ and may even be correlated with contemporaneous or lagged idiosyncratic errors (Roodman 2009). This in turn means that the model suffers from dynamic panel bias as described by Nickell (1981) and Bond (2002), where lagged dependent variables are endogenous to the fixed effects in panels with many cross-sectional units (*N*) but a small number of time periods (*T*). Estimating this model with OLS or fixed effects will therefore produce biased and inconsistent estimates. System GMM, developed by Arellano & Bover (1995) and Blundell & Bond (1998), provides a robust solution to this problem. They first transform the model (4) by first-differencing such as:

$$\Delta y_{i,t} = \beta_0 + \beta_1 \Delta y_{i,t-1} + \beta_2 \Delta CPU_{t-1} + \beta \Delta_2 X'_{i,t-k} + \Delta\varepsilon_{i,t} \tag{6}$$

This is our *First-Differenced* equation, where $\Delta y_{i,t} = (y_{i,t} - y_{i,t-1})$ and similarly for other variables. With this we've removed individual fixed effects that were correlated with the lagged dependent variable, however $\Delta y_{i,t-1}$ and $\Delta\varepsilon_{i,t}$ remain correlated. Anderson & Hsiao (1981) and Arellano & Bond (1991) suggest using lagged levels of our dependent variable ($y_{i,t-2}$, $y_{i,t-3}$, etc.) as instruments for the *First-Differenced* equation, but this approach is valid only if we assume that the lagged levels are not correlated with the error term. This one-step GMM model suffers from poor finite sample properties, primarily caused by lagged levels being weak predictors of the first differences (Blundell & Bond, 1998; Roodman, 2009). System GMM builds on this proposed model by adding an additional set of moment conditions. First, for our *First-Differenced* equation we use lagged levels of our endogenous variable $y_{i,t-1}$ as instruments for $\Delta y_{i,t-1}$. Second, for the *Level* equation we use lagged differences $\Delta y_{i,t-1}$ of our endogenous variable as instruments for $y_{i,t-1}$, assuming that the difference of our lagged variable is not correlated with the fixed effects. System GMM then combines our *Level* equation with the *First-Differenced* equation, increasing the number of instruments and consequently the efficiency of the estimations since the problem of weak instruments from before is now eliminated (Bun & Sarafidis, 2015). This dual approach is why the system GMM is also known as two-step GMM estimation (Roodman, 2009) and is often used a robustness check in related research (Ilyas et al., 2022; Nguyen & Trinh, 2023; Ongsakul et al., 2023). We report the diagnostic tests and the results of our GMM estimation in subchapter 5.3.

Results

5.1. The impact of CPU on firm-level variables

Table 3 and Table 4 show the results of estimating our main model given in equation (2). First column for each dependent variable, or odd numbered columns, report the results for the baseline equation where CPU and EPU's are lagged by only one period. Even numbered columns reports results with additional two year lag for each index value. Firm and sector-specific fixed effects are added to account for potential differential trends in-between firms and sectors, respectively. The coefficient for CPU is negative at lag 1 for ROE and R&D, but positive at lag 2, as seen in Table 3. These positive coefficients are statistically insignificant, however this change in direction might mean that increase in climate uncertainty may increase investments in research and development and lead to higher ROE in the long-term. When it comes to ROA, CPU is negative across all specifications and lags. By looking at column (1) in Table 3 we can see that that the coefficient for CPU is -0.001, indicating that an increase in CPU by one percent at time *t-1* is associated with a decrease in ROA by 0.001 percent at time *t*, holding other factors constant. When it comes to our EPU indices, EPU for US is negative and significant at 1% for ROA and ROE but positive for R&D, again implying that firms in the UK might interpret economic policy uncertainty in the US as a signal to increase investments in their research and development. When it comes to UK's EPU, the results vary depending on our lag specifications. This change in direction of coefficients for EPU might be because of a delayed response of firm variables to policy uncertainty, or a sign that adding too many lags for UK's EPU introduces noise into our model, and the issue is econometric in nature. The rest of our control variables are positive in year *t* and negative in year *t-1*, suggesting that last year's economic environment negatively affects firm's profitability and R&D expenditure.

CPU is uniformly negative in value across all investment variables in Table 4, with significane ranging from 5% and 10% for short-term investments to 1% significance for firm investments. CPU coefficient at lag 2 for firm investments is highly significant, showing that an increase in CPU at time *t-1* by one percent is associated with a decrease in firm investments by 0.008 percent, whereas a one-unit increase in CPU at time *t-2* decreases invesements by 0.006 percent. Both results are significant at 1% level. Important to note is that CPU and EPU_UK increase long-term investments, as seen in Table 4's columns (3) and (4), however these results are not statistically significant. US's EPU negatively affects investment variables, whereas UK's EPU index' sign changes depending on the lag, implying that the uncertainty affects investments with a lag as investments are usually planned long-term. Firm size and GDP rate follow the same trajectory, whereas the inflation rate usually affects investments negatively when significant.

To put our results into perspective, we look at CPU's coefficient for firm investments in Table 4 column (6), amounting to -0.008 in year *t-1*. The average value of firm investments across the firms in our sample is 80 million as seen in Table 2. The interpretation is then as follows: for a 1 percent increase in CPU in year *t-1*, the associated change in the dependent variable, our logarithm of firm investments, is -0.008% in year *t*, amounting to an average decrease of 6,400 british pounds, keeping all other variables fixed.

The results seem to be in line with previous literature that find similar negative relationship between CPU and firm variables (Berestycki et al., 2022; Ren et al., 2022a).

Table 3: Main analysis results (ROA, ROE, R&D expenditures)

Dependent variable	ROA (1)	ROA (2)	ROE (3)	ROE (4)	R&D (5)	R&D (6)
CPU	-0.001 *	-0.002 *	-0.000	-0.001 *	-0.002 **	-0.002 *
(one lag)	(0.059)	(0.068)	(0.811)	(0.061)	(0.021)	(0.059)
CPU		-0.001 *		0.001		0.000
(two lags)		(0.079)		(0.751)		(0.953)
EPU_UK	0.0001 ***	-0.001 ***	-0.001 ***	0.001	0.000	0.001
(one lag)	(0.009)	(0.000)	(0.006)	(0.155)	(0.815)	(0.576)
EPU_UK		-0.002 ***		0.001 **		0.001 **
(two lags)		(0.002)		(0.041)		(0.029)
EPU_US	-0.002 ***	-0.003 ***	-0.002 ***	-0.002 ***	0.001 ***	0.000 *
(one lag)	(0.001)	(0.000)	(0.000)	(0.004)	(0.004)	(0.096)
EPU_US		0.000		-0.001 ***		0.001 *
(two lags)		(0.228)		(0.004)		(0.083)
Firm Size	0.104 **	0.103 **	0.082 **	0.138 ***	0.316 ***	0.315 ***
	(0.026)	(0.027)	(0.025)	(0.001)	(0.000)	(0.000)
Firm Size	-0.237 ***	-0.238***	-0.151 ***	-0.169 ***	0.234 ***	0.233 ***
(one lag)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP rate	0.016 ***	0.0205 ****	0.021 ***	0.026 ***	-0.001	0.006
	(0.000)	(0.000)	(0.000)	(0.000)	(0.695)	(0.467)
GDP rate	-0.021***	-0.025 ***	-0.008	-0.022 **	0.004	0.0028
(one lag)	(0.000)	(0.000)	(0.126)	(0.000)	(0.458)	(0.779)
Inflation rate	0.039 ***	0.020 *	0.002	0.032 *	0.002	0.025
	(0.000)	(0.099)	(0.885)	(0.070)	(0.571)	(0.467)
Inflation rate	-0.021 ***	-0.033 ***	0.0124 *	0.051 ***	0.016 *	0.033 **
(one lag)	(0.000)	(0.004)	(0.063)	(0.001)	(0.094)	(0.031)
Constant	-1.984	-1.934 ***	-1.494	-1.274	-1.353	-1.324
R-squared	0.480	0.481	0.592	0.607	0.63	0.63
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
No. of obs	13,377	13,377	7,446	7,147	2,400	2,400

Note: Significance levels: *p<0.10; **p<0.05; ***p<0.01. Standard errors clustered at the firm level are in parentheses. All regressions include firm- and sector- fixed effects. Variables are winsorized at 1% and 99% levels

Table 4: Main analysis results (Short-term, Long-term and Firm investments)

Dependent variable	Short-term investments (1)	Short-term investments (2)	Long-term investments (3)	Long-term investments (4)	Firm Investments (5)	Firm Investments (6)
CPU	-0.002 **	-0.001 *	0.001	0.001	-0.009 ***	-0.008 ***
(one lag)	(0.041)	(0.052)	(0.198)	(0.230)	(0.000)	(0.000)
CPU		-0.002 **		0.002 *		-0.006 ***
(two lags)		(0.017)		(0.057)		(0.000)
EPU_UK	0.005 **	-0.001 *	0.003	0.000	0.001 *	0.002 ***
(one lag)	(0.046)	(0.061)	(0.314)	(0.299)	(0.085)	(0.000)
EPU_UK		-0.001		-0.001		-0.002 ***
(two lags)		(0.839)		(0.107)		(0.000)
EPU_US	-0.002 **	-0.001 *	-0.001 *	-0.001	-0.002 ***	-0.006 ***
(one lag)	(0.021)	(0.098)	(0.087)	(0.121)	(0.000)	(0.000)
EPU_US		-0.002 **		-0.002 *		-0.001
(two lags)		(0.025)		(0.065)		(0.981)
Firm Size	0.545 ***	0.548 ***	0.734 ***	0.732 ***	0.101 *	0.094
	(0.000)	(0.000)	(0.000)	(0.000)	(0.093)	(0.122)
Firm Size	0.024 **	0.131 **	0.126 **	0.125 **	-0.028 **	-0.028 **
(one lag)	(0.010)	(0.025)	(0.012)	(0.013)	(0.031)	(0.050)
GDP rate	-0.031 ***	-0.014 **	0.001	0.007	0.007	0.015 **
	(0.006)	(0.037)	(0.311)	(0.219)	(0.263)	(0.033)
GDP rate	-0.035 **	-0.017 **	-0.003	-0.003	0.014 **	0.007**
(one lag)	(0.019)	(0.023)	(0.617)	(0.105)	(0.020)	(0.036)
Inflation rate	0.072	0.030 *	0.002	0.023	-0.001	-0.059 **
	(0.106)	(0.062)	(0.171)	(0.061)	(0.962)	(0.024)
Inflation rate	-0.028	-0.274	0.003 ***	0.016 **	-0.086 ***	-0.091 ***
(one lag)	(0.499)	(0.582)	(0.000)	(0.046)	(0.000)	(0.000)
Constant	-0.368	-0.352	-2.033	-1.96	0.798	1.003
R-squared	0.69	0.69	0.60	0.60	0.76	0.77
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
No. of obs	4,239	4,239	12,007	12,007	13,441	13,441

Note: Significance levels: *p<0.10; **p<0.05; ***p<0.01. Standard errors clustered at the firm level are in parentheses. All regressions include firm- and sector- fixed effects. Variables are winsorized at 1% and 99% levels.

5.2. Results of the sensitivity analysis

Table 5 and Table 6 show the results of estimating our models (3) and (4). Odd-numbered columns show the results of interacting CPU with our ESG variable in order to assess whether ESG can mediate CPU's presumably negative effects on dependent variables. Across all dependent variables, CPU's interaction term with ESG is negative and overall significant. For example, the result for ROA in Table 5, column 1, tells us that for a given log change in CPU, the log change in the dependent variable decreases by 0.024 times the log of the ESG score. The marginal effect is that the higher ESG score lowers the impact of changes in CPU on $y_{i,t}$. This result is significant at 10%, whereas for other variables, such as R&D expenditures, and firm investments the significance is at 5%. Interaction variable between EPU indices and ESG scores are negative for ROA and ROE but positive for R&D, indicating that ESG helps mediate EPU's adverse affects. When it comes to our investment variables, ESG seems to lower negative effects of EPU indices at 5% and 10% levels of significance. The rest of our control variables are not interacted with ESG, and have varying effects on our outcome variables, usually positive in year *t* but negative effect in year *t-1*. These results are line with our predictions based on the similar works of (Azimli, 2023; Ilyas et al., 2022).

Even-numbered columns have as main independent variable the interaction between CPU and CO2 emissions, in order to answer the question whether CPU has a greater effect on dependent variables depending on the level of CO2 exposure. In this case, coefficients are positive, with most of them significant at 10% level. Taking for example Table 6, column 2, we can interpret that for a given log change in CPU the log change in short-term investments increases by 0.034 times the log of the CO2 emissions value. The marginal effect is then such that the higher CO2 score increases the impact of changes in CPU on our dependent variables, and the results are uniform in their direction. Coefficients for our EPU indices are positive, suggesting that high CO2 emissions exacerbate effects of economic policy uncertainty on firm variables. That does not seem to hold in the case of R&D expenditures where coefficients for our EPU indices are negative, implying that the higher the CO2 emissions the greater the R&D expenditures. We could interpret that as firms investing in projects that may lower their CO2 emissions in the future, as it is important to bear in mind that CO2 emissions are self-reported and not all firms chose to report it. Hence, the sample is skewed towards firms that are taking their CO2 emissions and future sustainability practices seriously.

Table 5: Results of sensitivity analysis for ESG and CO2 (ROA, ROE, R&D expenditure)

Dependent variable	ROA (1)	ROA (2)	ROE (3)	ROE (4)	R&D (5)	R&D (6)
CPU x ESG	-0.024 * (0.094)		-0.018 (0.093) *		-0.054 ** (0.037)	
CPU x CO2		0.039 * (0.067)		0.045 * (0.087)		0.082 *** (0.001)
EPU_UK	-0.013 (0.419)	0.036 * (0.084)	0.016 * (0.090)	0.033 * (0.066)	0.048 (0.205)	-0.056 (0.312)
EPU_US	-0.027 *** (0.001)	0.029 *** (0.010)	0.012 * (0.061)	0.046 ** (0.043)	0.015 ** (0.039)	-0.018 * (0.093)
Firm Size	-0.012 * (0.056)	-0.019 ** (0.019)	-0.024 (0.546)	-0.041 (0.595)	0.039 *** (0.005)	0.043 ** (0.029)
Firm Size *(one lag)*	0.041 (0.572)	0.012 (0.162)	-0.042 (0.342)	-0.026 ** (0.035)	-0.029 ** (0.014)	-0.035 * (0.044)
GDP rate	0.020 ** (0.011)	-0.013 (0.175)	0.017 *** (0.000)	0.016 *** (0.001)	0.012 (0.479)	0.021 (0.294)
GDP rate *(one lag)*	-0.012 *** (0.007)	-0.008 * (0.083)	-0.012 ** (0.013)	-0.009 ** (0.021)	-0.012 * (0.094)	-0.011 ** (0.017)
Inflation rate	0.028 *** (0.002)	0.027 *** (0.003)	0.020 *** (0.008)	0.020 *** (0.010)	0.005 (0.728)	0.003 (0.877)
Inflation rate *(one lag)*	-0.051 *** (0.000)	-0.050 *** (0.000)	-0.012 (0.159)	-0.010 (0.263)	-0.22 (0.360)	0.034 (0.245)
Constant	0.645	0.562	0.525	0.447	-0.78	-0.77
R-squared	0.18	0.19	0.18	0.20	0.13	0.17
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
No. of obs	3,689	2,759	3,637	2,905	685	539

Note: Significance levels: *p<0.10; **p<0.05; ***p<0.01. Standard errors clustered at the firm level are in parentheses. All regressions include firm-, sector- and time- fixed effects. Variables are winsorized at 1% and 99% levels.

Table 6: Results of sensitivity analysis for ESG and CO2 (Short-term, Long-term and Firm investments)

Dependent variable	Short-term investments (1)	Short-term investments (2)	Long-term investments (3)	Long-term investments (4)	Firm Investments (5)	Firm Investments ()
CPU x ESG	-0.046 *		-0.084 **		-0.067 **	
	(0.072)		(0.032)		(0.047)	
CPU x CO2		0.034 *		0.058 **		0.025 *
		(0.073)		(0.049)		(0.063)
EPU_UK	-0.049 *	0.015 **	-0.058 *	0.060 *	-0.013 *	0.014 *
	(0.056)	(0.026)	(0.079)	(0.091)	(0.077)	(0.079)
EPU_US	-0.015 **	0.025 **	-0.018 *	0.006 *	-0.021 **	0.036
	(0.053)	(0.023)	(0.085)	(0.094)	(0.030)	(0.102)
Firm Size	0.055 ***	0.054 ***	0.066 ***	0.069 **	0.021 ***	0.022 ***
	(0.003)	(0.004)	(0.000)	(0.015)	(0.000)	(0.000)
Firm Size	-0.054 ***	-0.045 ***	-0.068 ***	-0.070 ***	0.024 ***	-0.025 ***
(one lag)	(0.003)	(0.008)	(0.000)	(0.009)	(0.000)	(0.000)
GDP rate	-0.017 **	-0.006 *	0.002 **	0.005 **	0.024	0.015
	(0.027)	(0.072)	(0.072)	(0.042)	(0.111)	(0.354)
GDP rate	-0.005	-0.003	0.007	0.011 *	0.026 **	0.012 **
(one lag)	(0.655)	(0.781)	(0.208)	(0.087)	(0.016)	(0.035)
Inflation rate	0.025 **	0.014 *	-0.009 **	-0.014 **	-0.038 **	-0.001 *
	(0.041)	(0.067)	(0.040)	(0.031)	(0.011)	(0.096)
Inflation rate	-0.034	-0.11	-0.001	-0.002	0.017	0.001
(one lag)	(0.453)	(0.821)	(0.887)	(0.875)	(0.541)	(0.788)
Constant	-0.150	-0.770	-0.206	0.084	0.858	1.600
R-squared	0.11	0.10	0.12	0.11	0.18	0.21
Prob > F	0.000	0.000	0.000	0.000	0.000	0.000
No. of obs	1,243	981	3,348	2,447	2,491	1,821

Note: Significance levels: *p<0.10; **p<0.05; ***p<0.01. Standard errors clustered at the firm level are in parentheses. All regressions include firm-, sector- and time- fixed effects. Variables are winsorized at 1% and 99% level

5.3. Robustness check results

A unit root test for stationarity of our data is performed before running the GMM model, as mean stationarity assumption is imperative for avoiding spurious regressios in System GMM model (Bun & Sarafidis, 2015). The unit root test rejects stationarity for all our regressions. The Hansen test of overidentifying restrictions checks the validity of our instruments and is given in Table A1 along with the rest of our diagnostic tests. The high p-value ($p>0.05$) confirms that our instruments are valid. Since we are estimating a System GMM we test validity of instruments used for the *Level* equation as well, also known as the Difference-in-Hansen test (Roodman, 2009). We reject the null hypothesis that the instruments are invalid at $p>0.05$. Finally we report tests for the presence of first- and second- order autocorrelation in first-differenced errors: AR(1) and AR(2) respectively. Significant values for AR(1) test suggest that there is no serial correlation problem. For AR(2) test, high p-values confirm that differenced residuals do not exhibit AR(2) autocorrelation, as that would render them inappropriate (Bun & Sarafidis, 2015).

The coefficient for our lagged dependent variables generated by the GMM are expected to be between 0 and 1, as that would indicate that the results correctly lie between the results of OLS and fixed effects estimators (Bun & Sarafidis, 2015). Table A1 confirms that to be the case and all are significant at 1% level. This also tells us that our firm-level variables are influenced by their values from past periods. Our CPU variable exhibits similar results as in our fixed effects estimation, with values being negative and significant at 10% and 5% level. For example, a one percent increase in CPU decreases short-term investments by 0.001 percent, keeping all other variables fixed. Coefficients for EPU indices are uniformly negative at one period lag, and statistically significant. The results of our two-step GMM model seem to be similar to our fixed effects estimation, validating our overall results that CPU should negatively affect our firm-level variables.

Conclusion

This thesis aims to determine whether US climate policy uncertainty affects the behavior of firms in the UK, focusing on cross-country policy uncertainty spillovers. We construct a panel dataset on UK firm-level variables such as investments and profitability ratios, utilizing the Climate Policy Uncertainty (CPU) index to proxy US-based climate policy uncertainty. To address endogeneity issues, we employ fixed effects estimation and a System GMM model, estimating the effects of CPU on firm-level variables. Our findings, although small, are statistically significant, indicating some spillover of climate policy uncertainty on UK firms, particularly affecting their investments in fixed assets.

In the second part of our analysis we assess potential firm factors that could exacerbate or mitigate the suggested In the second part of our analysis, we assess potential firm factors that could exacerbate or mitigate the adverse effects of climate policy uncertainty. We hypothesize that firms with higher CO2 emissions suffer greater adverse effects of CPU, which our results support. Conversely, firms investing in climate social responsibility, proxied by their ESG scores, appear to mitigate the adverse effects of CPU. Our results suggest that these firms do not postpone their R&D expenditures or other investments despite uncertainty. This finding supports similar research on the subject of firm investment into CSR being beneficial for businesses by (Zhang et al., 2024)

This research contributes to the CPU literature by demonstrating that the CPU index can be used to investigate spillover effects of climate policy uncertainty on firms outside the US. Given the US's leading role in proposing climate change policies, uncertainty in their implementation affects policies in other countries and, for the UK, business decisions. Additionally, our study expands the topic of CPU by assessing whether its adverse effects can be mitigated by investing in climate social responsibility practices. These findings have significant implications for researchers and firms in the UK and globally. While previous research calls on policymakers to be more transparent and collaborate with the private sector to reduce uncertainty in policymaking, our study shows that firms can also mitigate the impact of climate policy uncertainty by proactively investing in climate social responsibility. This approach shifts firms from merely reacting to uncertainty to actively countering its effects.

The limitations of this study include the novel nature of the CPU index, which has yet to be thoroughly researched and constructed for other countries besides the US. Additionally, our sample consists only of publicly traded companies, which may not be representative of all UK firms. The lack of comprehensive data on CO_2 emissions for all firms may skew our sample towards high emitters that are actively seeking to reduce their emissions.

Future research could investigate the effects of CPU on other economies, particularly those closely connected to the US, such as Canada and Mexico. It could also explore differential effects of CPU across sectors and assess how ESG investments mitigate CPU's effects, providing valuable insights for stakeholders worldwide.

References

Abel, A. B. (1983). Optimal Investment Under Uncertainty, *The American Economic Review*, [e-journal] vol. 73, no. 1, pp.228–233, Available Online: https://www.jstor.org/stable/1803942 [Accessed 17 May 2024]

Ali, K., Hongbing, H., Liew, C. Y. & Jianguo, D. (2023). Governance Perspective and the Effect of Economic Policy Uncertainty on Financial Stability: Evidence from Developed and Developing Economies, *Economic Change and Restructuring*, [e-journal] vol. 56, no. 3, pp.1971–2002, Available Online: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10020074/ [Accessed 17 May 2024]

Al-Thaqeb, S. A. & Algharabali, B. G. (2019). Economic Policy Uncertainty: A Literature Review, *The Journal of Economic Asymmetries*, [e-journal] vol. 20, no. C, Available Online: https://econpapers.repec.org/article/eeejoecas/v_3a20_3ay_3a2019_3ai_3ac_3as1703494919300726.htm [Accessed 17 May 2024]

Anderson, T. W. & Hsiao, C. (1981). Estimation of Dynamic Models with Error Components, *Journal of the American Statistical Association*, [e-journal] vol. 76, no. 375, pp.598–606, Available Online: https://www.jstor.org/stable/2287517 [Accessed 24 May 2024]

Angrist, J. & Pischke, J.-S. (2009). Mostly Harmless Econometrics: An Empiricist's Companion, in *Mostly Harmless Econometrics: An Empiricist's Companion*

AR5 Synthesis Report: Climate Change 2014 — IPCC. (2024). , Available Online: https://www.ipcc.ch/report/ar5/syr/ [Accessed 17 April 2024]

Arellano, M. & Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-Components Models, *Journal of Econometrics*, [e-journal] vol. 68, no. 1, pp.29–51, Available Online: https://www.sciencedirect.com/science/article/pii/030440769401642D [Accessed 24 May 2024]

Ayed, S., Ben-Amar, W. & Arouri, M. (2024). Climate Policy Uncertainty and Corporate Dividends, *Finance Research Letters*, [e-journal] vol. 60, p.104948, Available Online: https://www.sciencedirect.com/science/article/pii/S154461232301320X [Accessed 17 April 2024]

Azimli, A. (2023). The Impact of Climate Policy Uncertainty on Firm Value: Does Corporate Social Responsibility Engagement Matter?, *Finance Research Letters*, [e-journal] vol. 51, p.103456, Available Online: https://www.sciencedirect.com/science/article/pii/S1544612322006328 [Accessed 17 April 2024]

Baker, S. R., Bloom, N. & Davis, S. J. (2016). Measuring Economic Policy Uncertainty*, *The Quarterly Journal of Economics*, [e-journal] vol. 131, no. 4, pp.1593–1636, Available Online: https://doi.org/10.1093/qje/qjw024 [Accessed 9 April 2024]

Berestycki, C., Carattini, S., Dechezleprêtre, A. & Kruse, T. (2022). Measuring and Assessing the Effects of Climate Policy Uncertainty, Paris: OECD, Available Online: https://www.oecd-ilibrary.org/economics/measuring-and-assessing-the-effects-of-climate-policy-uncertainty_34483d83-en [Accessed 17 May 2024]

Bernanke, B. S. (1983). Irreversibility, Uncertainty, and Cyclical Investment, *The Quarterly Journal of Economics*, [e-journal] vol. 98, no. 1, pp.85–106, Available Online: https://www.jstor.org/stable/1885568 [Accessed 23 May 2024]

Biljanovska, N., Grigoli, F. & Hengge, M. (2021). Fear Thy Neighbor: Spillovers from Economic Policy Uncertainty, *Review of International Economics*, [e-journal] vol. 29, no. 2, pp.409–438, Available Online: https://ideas.repec.org//a/bla/reviec/v29y2021i2p409-438.html [Accessed 17 April 2024]

Bloom, N. (2009). The Impact of Uncertainty Shocks, *Econometrica*, [e-journal] vol. 77, no. 3, pp.623–685, Available Online: https://onlinelibrary.wiley.com/doi/abs/10.3982/ECTA6248 [Accessed 17 May 2024]

Blundell, R. & Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics*, [e-journal] vol. 87, no. 1, pp.115–143, Available Online: https://ideas.repec.org//a/eee/econom/v87y1998i1p115-143.html [Accessed 24 May 2024]

Bond, S. R. (2002). Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice, *Portuguese Economic Journal*, [e-journal] vol. 1, no. 2, pp.141–162, Available Online: https://doi.org/10.1007/s10258-002-0009-9 [Accessed 13 May 2024]

Brooks, C. (2019). Introductory Econometrics for Finance, *Higher Education from Cambridge University Press*, Available Online: https://www.cambridge.org/highereducation/books/introductory-econometrics-for-finance/75E9C608EA95A3AD87FB3BC683B9EBBF [Accessed 17 May 2024]

Bun, M. J. G. & Sarafidis, V. (2015). Dynamic Panel Data Models, in B. H. Baltagi (ed.), *The Oxford Handbook of Panel Data*, [e-book] Oxford University Press, p.0, Available Online: https://doi.org/10.1093/oxfordhb/9780199940042.013.0003 [Accessed 22 May 2024]

Chen, Z., Zhang, L. & Weng, C. (2023). Does Climate Policy Uncertainty Affect Chinese Stock Market Volatility?, *International Review of Economics & Finance*, [e-journal] vol. 84, no. C, pp.369–381, Available Online: https://ideas.repec.org//a/eee/reveco/v84y2023icp369-381.html [Accessed 17 April 2024]

Cho, D., Kim, H. & Lee, K. (2023). Dynamic Spillovers of Economic Policy Uncertainty Across the US, Europe, and East Asia, *Global Economic Review*, [e-journal] vol. 52, no. 3, pp.187–201, Available Online: https://doi.org/10.1080/1226508X.2023.2243066 [Accessed 17 May 2024]

Christou, C., Cunado, J., Gupta, R. & Hassapis, C. (2017). Economic Policy Uncertainty and Stock Market Returns in PacificRim Countries: Evidence Based on a Bayesian Panel VAR Model, *Journal of Multinational Financial Management*, [e-journal] vol. 40, no. C, pp.92–102, Available Online: https://econpapers.repec.org/article/eeemulfin/v_3a40_3ay_3a2017_3ai_3ac_3ap_3a92-102.htm [Accessed 23 May 2024]

Clausen, V., Schlösser, A. & Thiem, C. (2019). Economic Policy Uncertainty in the Euro Area: Cross-Country Spillovers and Macroeconomic Impact, *Jahrbücher für Nationalökonomie und Statistik*, [e-journal] vol. 239, no. 5–6, pp.957–981, Available Online: https://www.degruyter.com/document/doi/10.1515/jbnst-2018-0083/html [Accessed 10 April 2024]

Climate Policy Uncertainty and Firms' and Investors' Behavior | TSE. (2022). , Available Online: https://www.tse-fr.eu/publications/climate-policy-uncertainty-and-firms-and-investors-behavior [Accessed 17 April 2024]

Da, Z., Engelberg, J. & Gao, P. (2015). The Sum of All FEARS Investor Sentiment and Asset Prices, *Review of Financial Studies*, vol. 28, pp.1–32

Dkhili, H. (2023). Does Environmental, Social and Governance (ESG) Affect Market Performance? The Moderating Role of Competitive Advantage, *Competitiveness Review: An International Business Journal*, [e-journal] vol. 34, no. 2, pp.327–352, Available Online: https://doi.org/10.1108/CR-10-2022-0149 [Accessed 17 May 2024]

Engle, R., Giglio, S., Lee, H., Kelly, B. & Stroebel, J. (2019). Hedging Climate Change News, *SSRN Electronic Journal*

Farooq, U., Tabash, M. I., Anagreh, S. & Al-Faryan, M. A. S. (2022). Economic Policy Uncertainty and Corporate Investment: Does Quality of Governance Matter?, *Cogent Economics & Finance*, [e-journal], Available Online: https://www.tandfonline.com/doi/abs/10.1080/23322039.2022.2157118 [Accessed 17 May 2024]

Frank H. Knight. (1921). Risk, Uncertainty, and Profit | Online Library of Liberty, Available Online: https://oll.libertyfund.org/titles/knight-risk-uncertainty-and-profit [Accessed 17 May 2024]

Gavriilidis, K. (2021). Measuring Climate Policy Uncertainty, SSRN Scholarly Paper, 3847388, Available Online: https://papers.ssrn.com/abstract=3847388 [Accessed 9 April 2024]

Gholipour, H. F. (2019). The Effects of Economic Policy and Political Uncertainties on Economic Activities, *Research in International Business and Finance*, [e-journal] vol. 48, pp.210–218, Available Online: https://www.sciencedirect.com/science/article/pii/S0275531918306081 [Accessed 23 May 2024]

González-Marrón, A., Martín-Sánchez, J. C. & Martínez-Sánchez, J. M. (2020). Current and Future Perspectives in Lung Cancer Prevention, 0, *Precision Cancer Medicine*, [e-journal] vol. 3, no. 0, Available Online: https://pcm.amegroups.com/article/view/5724 [Accessed 12 October 2022]

Guesmi, K., Makrychoriti, P. & Spyrou, S. (2023). The Relationship between Climate Risk, Climate Policy Uncertainty, and CO2 Emissions: Empirical Evidence from the US, *Journal of Economic Behavior & Organization*, [e-journal] vol. 212, pp.610–628, Available Online: https://www.sciencedirect.com/science/article/pii/S0167268123002214 [Accessed 17 April 2024]

Gulen, H. & Ion, M. (2016). Policy Uncertainty and Corporate Investment, *The Review of Financial Studies*, [e-journal] vol. 29, no. 3, pp.523–564, Available Online: https://doi.org/10.1093/rfs/hhv050 [Accessed 17 May 2024]

Guo, P., Zhu, H. & You, W. (2018). Asymmetric Dependence between Economic Policy Uncertainty and Stock Market Returns in G7 and BRIC: A Quantile Regression Approach, *Finance Research Letters*, [e-journal] vol. 25, no. C, pp.251–258, Available Online: https://ideas.repec.org//a/eee/finlet/v25y2018icp251-258.html [Accessed 23 May 2024]

hakim. (2023). Economic Update: Short Recession Looming and Concern over US Climate Policies, [e-journal], Available Online: https://commonslibrary.parliament.uk/economic-update-short-recession-looming-and-concern-over-us-climate-policies/ [Accessed 23 May 2024]

How to Do Xtabond2: An Introduction to Difference and System GMM in Stata - David Roodman, 2009. (2024). , Available Online: https://journals.sagepub.com/doi/10.1177/1536867X0900900106 [Accessed 24 May 2024]

Huang, T. & Sun, Z. (n.d.). Climate Policy Uncertainty and Firm Investment, *International Journal of Finance & Economics*, [e-journal] vol. n/a, no. n/a, Available Online: https://onlinelibrary.wiley.com/doi/abs/10.1002/ijfe.2881 [Accessed 17 May 2024]

Ilyas, M., Mian, R. U. & Suleman, M. T. (2022). Economic Policy Uncertainty and Firm Propensity to Invest in Corporate Social Responsibility, *Management Decision*, [e-journal] vol. 60, no. 12, pp.3232–3254, Available Online: https://doi.org/10.1108/MD-06-2021-0746 [Accessed 17 April 2024]

Im, H. J., Park, H. & Zhao, G. (2017). Uncertainty and the Value of Cash Holdings, *Economics Letters*, [e-journal] vol. 155, pp.43–48, Available Online: https://www.sciencedirect.com/science/article/pii/S016517651730099X [Accessed 17 May 2024]

Iqbal, U., Gan, C. & Nadeem, M. (2020). Economic Policy Uncertainty and Firm Performance, *Applied Economics Letters*, [e-journal] vol. 27, no. 10, pp.765–770, Available Online: https://doi.org/10.1080/13504851.2019.1645272 [Accessed 17 May 2024]

Jacobson, R. (1990). Unobservable Effects and Business Performance, *Marketing Science*, [e-journal] vol. 9, no. 1, pp.74–85, Available Online: https://www.jstor.org/stable/183956 [Accessed 14 May 2024]

Jens, C. E. (2017). Political Uncertainty and Investment: Causal Evidence from U.S. Gubernatorial Elections, *Journal of Financial Economics*, [e-journal] vol. 124, no. 3, pp.563–579, Available Online: https://www.sciencedirect.com/science/article/pii/S0304405X17300582 [Accessed 17 May 2024]

Jurado, K., Ludvigson, S. C. & Ng, S. (2015). Measuring Uncertainty, *American Economic Review*, [e-journal] vol. 105, no. 3, pp.1177–1216, Available Online: https://www.aeaweb.org/articles?id=10.1257/aer.20131193 [Accessed 17 May 2024]

Lasisi, L., Omoke, P. C. & Salisu, A. A. (2022). Climate Policy Uncertainty and Stock Market Volatility, *Asian Economics Letters*, [e-journal] vol. 5, no. Early View, Available Online: https://a-e-l.scholasticahq.com/article/37246-climate-policy-uncertainty-and-stock-market-volatility [Accessed 17 April 2024]

Lavelle, M. (2020). Ignoring Scientists' Advice, Trump's EPA Rejects Stricter Air Quality Standard, *Inside Climate News*, Available Online: https://insideclimatenews.org/news/15042020/air-pollution-epa-covid-pm2-5-secret-science-rule-health-fuel-standard-climate-change/ [Accessed 13 May 2024]

Liu, L. & Zhang, T. (2015). Economic Policy Uncertainty and Stock Market Volatility, *Finance Research Letters*, [e-journal] vol. 15, pp.99–105, Available Online: https://www.sciencedirect.com/science/article/pii/S1544612315000835 [Accessed 17 May 2024]

Lv, W. & Li, B. (2023). Climate Policy Uncertainty and Stock Market Volatility: Evidence from Different Sectors, *Finance Research Letters*, [e-journal] vol. 51, p.103506, Available Online: https://www.sciencedirect.com/science/article/pii/S1544612322006821 [Accessed 17 April 2024]

Mahjoubi, M. & Henchiri, J. E. (2023). Policy Uncertainty and the Volatility of the S&P 500: Before and After the Launch of the S&P 500 ESG, 11, *International Journal of Economics and Finance*, [e-journal] vol. 15, no. 11, p.p28, Available Online: https://ccsenet.org/journal/index.php/ijef/article/view/0/49360 [Accessed 17 April 2024]

Nguyen, M. H. & Trinh, V. Q. (2023). U.K. Economic Policy Uncertainty and Innovation Activities: A Firm-Level Analysis, *Journal of Economics and Business*, [e-journal] vol. 123, p.106093, Available Online: https://www.sciencedirect.com/science/article/pii/S0148619522000492 [Accessed 17 April 2024]

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects, *Econometrica*, [e-journal] vol. 49, no. 6, pp.1417–1426, Available Online: https://www.jstor.org/stable/1911408 [Accessed 7 May 2024]

Niu, S., Zhang, J., Luo, R. & Feng, Y. (2023). How Does Climate Policy Uncertainty Affect Green Technology Innovation at the Corporate Level? New Evidence from China, *Environmental Research*, [e-journal] vol. 237, p.117003, Available Online: https://www.sciencedirect.com/science/article/pii/S0013935123018078 [Accessed 17 April 2024]

Ongsakul, V., Papangkorn, S. & Jiraporn, P. (2023). Estimating the Effect of Climate Change Exposure on Firm Value Using Climate Policy Uncertainty: A Text-Based Approach, *Journal of Behavioral and Experimental Finance*, [e-journal] vol. 40, p.100842, Available Online: https://www.sciencedirect.com/science/article/pii/S2214635023000564 [Accessed 17 April 2024]

Persakis, A. (2023). The Impact of Climate Policy Uncertainty on ESG Performance, Carbon Emission Intensity and Firm Performance: Evidence from Fortune 1000 Firms, *Environment, Development and Sustainability*, [e-journal], Available Online: https://doi.org/10.1007/s10668-023-03634-x [Accessed 17 April 2024]

Phan, D. H. B., Sharma, S. S. & Tran, V. T. (2018). Can Economic Policy Uncertainty Predict Stock Returns? Global Evidence, *Journal of International Financial Markets, Institutions and Money*, [e-journal] vol. 55, pp.134–150, Available Online: https://www.sciencedirect.com/science/article/pii/S1042443117301786 [Accessed 17 May 2024]

Raza, S. A., Khan, K. A., Benkraiem, R. & Guesmi, K. (2024). The Importance of Climate Policy Uncertainty in Forecasting the Green, Clean and Sustainable Financial Markets Volatility, *International Review of Financial Analysis*, [e-journal] vol. 91, p.102984, Available Online: https://www.sciencedirect.com/science/article/pii/S1057521923005008 [Accessed 17 April 2024]

Ren, X., Shi, Y. & Jin, C. (2022a). Climate Policy Uncertainty and Corporate Investment: Evidence from the Chinese Energy Industry, *Carbon Neutrality*, [e-journal] vol. 1, no. 1, p.14, Available Online: https://doi.org/10.1007/s43979-022-00008-6 [Accessed 24 May 2024]

Ren, X., Zhang, X., Yan, C. & Gozgor, G. (2022b). Climate Policy Uncertainty and Firm-Level Total Factor Productivity: Evidence from China, *Energy Economics*, [e-journal] vol. 113, p.106209, Available Online: https://www.sciencedirect.com/science/article/pii/S0140988322003577 [Accessed 17 April 2024]

Roberts, M. R. & Whited, T. M. (2012). Endogeneity in Empirical Corporate Finance, SSRN Scholarly Paper, 1748604, Available Online: https://papers.ssrn.com/abstract=1748604 [Accessed 17 May 2024]

Schober, P., Boer, C. & Schwarte, L. A. (2018). Correlation Coefficients: Appropriate Use and Interpretation, *Anesthesia & Analgesia*, [e-journal] vol. 126, no. 5, p.1763, Available Online: https://journals.lww.com/anesthesia-analgesia/fulltext/2018/05000/correlation_coefficients__appropriate_use_and.50.aspx [Accessed 13 May 2024]

Sorbe, S. & Johansson, Å. (2017). International Tax Planning, Competition and Market Structure, Paris: OECD, Available Online: https://www.oecd-ilibrary.org/economics/international-tax-planning-competition-and-market-structure_e9c35474-en [Accessed 17 May 2024]

Sritharan, V. (2015). Does Firm Size Influence on Firm's Profitability? Evidence from Listed Firms of Sri Lankan Hotels and Travels Sector, *Research Journal of Finance and Accounting*, [e-journal], Available Online: https://www.semanticscholar.org/paper/Does-firm-size-influence-on-firm%E2%80%99s-Profitability-of-Sritharan/4b5b3ba06993b6f77630d73de3e58caf9dd8056c [Accessed 17 May 2024]

Stock, J. H. & Watson, M. W. (2008). Heteroskedasticity-Robust Standard Errors for Fixed Effects Panel Data Regression, *Econometrica*, [e-journal] vol. 76, no. 1, pp.155–174, Available Online: https://onlinelibrary.wiley.com/doi/abs/10.1111/j.0012-9682.2008.00821.x [Accessed 12 May 2024]

Tedeschi, M., Foglia, M., Bouri, E. & Dai, P.-F. (2024). How Does Climate Policy Uncertainty Affect Financial Markets? Evidence from Europe, *Economics Letters*, [e-journal] vol. 234, p.111443, Available Online: https://www.sciencedirect.com/science/article/pii/S016517652300469X [Accessed 17 May 2024]

Trung, N. B. (2019). The Spillover Effects of US Economic Policy Uncertainty on the Global Economy: A Global VAR Approach, *The North American Journal of Economics and Finance*, [e-journal] vol. 48, pp.90–110, Available Online: https://www.sciencedirect.com/science/article/pii/S1062940818302523 [Accessed 12 May 2024]

Understanding ESG Data and Scores from Refinitiv | Issuer Services | LSEG. (2024). , Available Online: https://www.lsegissuerservices.com/spark/understanding-refinitiv-esg-data-scores/understanding-esg-data-and-scores-from-refinitiv [Accessed 15 May 2024]

Vural-Yavaş, Ç. (2021). Economic Policy Uncertainty, Stakeholder Engagement, and Environmental, Social, and Governance Practices: The Moderating Effect of Competition, *Corporate Social Responsibility and Environmental Management*, [e-journal] vol. 28, no. 1, pp.82–102, Available Online: https://onlinelibrary.wiley.com/doi/abs/10.1002/csr.2034 [Accessed 12 May 2024]

Wilcox, R. R. (2003). 3 - SUMMARIZING DATA, in R. R. Wilcox (ed.), *Applying Contemporary Statistical Techniques*, [e-book] Burlington: Academic Press, pp.55–91, Available Online: https://www.sciencedirect.com/science/article/pii/B9780127515410500249 [Accessed 7 May 2024]

Xu, Y. (2017). Generalized Synthetic Control Method: Causal Inference with Interactive Fixed Effects Models, *Political Analysis*, [e-journal] vol. 25, no. 1, pp.57–76, Available Online: https://www.cambridge.org/core/journals/political-analysis/article/generalized-synthetic-control-method-causal-inference-with-interactive-fixed-effects-models/B63A8BD7C239DD4141C67DA10CD0E4F3 [Accessed 4 January 2023]

Xu, Y., Wang, J., Chen, Z. & Liang, C. (2021). Economic Policy Uncertainty and Stock Market Returns: New Evidence, *The North American Journal of Economics and Finance*, [e-journal] vol. 58, p.101525, Available Online: https://www.sciencedirect.com/science/article/pii/S1062940821001418 [Accessed 23 May 2024]

Yousefi, H. & Yung, K. (2022). Financial Flexibility and Economic Policy Uncertainty: Evidence from Firm Behavior and Firm Value, *Journal of Corporate Accounting & Finance*, [e-journal] vol. 33, no. 1, pp.11–22, Available Online: https://onlinelibrary.wiley.com/doi/abs/10.1002/jcaf.22521 [Accessed 12 May 2024]

Yu, X. & Huang, Y. (2021). The Impact of Economic Policy Uncertainty on Stock Volatility: Evidence from GARCH–MIDAS Approach, *Physica A: Statistical Mechanics and its Applications*, [e-journal] vol. 570, no. C, Available Online: https://econpapers.repec.org/article/eeephsmap/v_3a570_3ay_3a2021_3ai_3ac_3as0378437121000662.htm [Accessed 23 May 2024]

Zhang, C., Farooq, U., Jamali, D. & Alam, M. M. (2024). The Role of ESG Performance in the Nexus between Economic Policy Uncertainty and Corporate Investment, *Research in International Business and Finance*, [e-journal] vol. 70, p.102358, Available Online: https://www.sciencedirect.com/science/article/pii/S027553192400151X [Accessed 12 May 2024]

Zhang, G., Han, J., Pan, Z. & Huang, H. (2015). Economic Policy Uncertainty and Capital Structure Choice: Evidence from China, *Economic Systems*, [e-journal] vol. 39, no. 3, pp.439–457, Available Online: https://www.sciencedirect.com/science/article/pii/S0939362515000448 [Accessed 17 May 2024]

Zhao, S. C., Nadeem Ilahi,Krzysztof Krogulski,Grace B. Li,Sabiha Mohona,Yueshu. (2024). Climate Change Mitigation and Policy Spillovers in the EU’s Immediate Neighborhood, *IMF*, Available Online: https://www.imf.org/en/Publications/WP/Issues/2023/11/30/Climate-Change-Mitigation-and-Policy-Spillovers-in-the-EUs-Immediate-Neighborhood-541902 [Accessed 23 May 2024]

Table A1: Results of the robustness check using the system-GMM model

Dependent variable	$y_{i,t}$ = ROA	$y_{i,t}$ = ROE	$y_{i,t}$ = R&D	$y_{i,t}$ = Short-term Investments	$y_{i,t}$ = Long-term Investments	$y_{i,t}$ = Firm Investments
$y_{i,t}$	0.159***	0.599***	0.640***	0.523***	0.780***	0.079***
(one lag)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.004)
CPU	-0.003*	-0.001*	-0.001*	-0.001**	0.001**	-0.007**
(one lag)	(0.036)	(0.078)	(0.052)	(0.043)	(0.210)	(0.015)
EPU_UK	-0.002***	-0.002*	-0.000**	-0.001**	-0.001*	-0.006**
(one lag)	(0.000)	(0.058)	(0.030)	(0.038)	(0.084)	(0.015)
EPU_US	-0.001*	-0.001*	-0.001**	-0.001*	-0.001***	-0.003*
(one lag)	(0.096)	(0.094)	(0.496)	(0.070)	(0.011)	(0.054)
Firm Size	0.194*	0.411**	0.652**	0.779***	0.674***	0.827**
	(0.072)	(0.045)	(0.013)	(0.000)	(0.000)	(0.042)
Firm Size	-0.089*	-0.577**	-0.404**	-0.419**	-0.496***	-0.350*
(one lag)	(0.083)	(0.021)	(0.025)	(0.000)	(0.000)	(0.073)
GDP rate	0.015*	0.028***	-0.020**	-0.019**	0.001*	0.017*
	(0.091)	(0.001)	(0.026)	(0.026)	(0.089)	(0.059)
GDP rate	-0.019	-0.018	-0.032**	-0.014	-0.007**	-0.086**
(one lag)	(0.155)	(0.176)	(0.026)	(0.161)	(0.047)	(0.012)
Inflation rate	0.048***	0.011**	-0.025	-0.024	-0.001	-0.105
	(0.005)	(0.049)	(0.258)	(0.284)	(0.861)	(0.592)
Inflation rate	-0.112***	-0.025**	-0.032	-0.041**	-0.008**	-0.086**
(one lag)	(0.000)	(0.036)	(0.263)	(0.012)	(0.037)	(0.016)
Hansen test	11.23	18.70	8.68	6.82	11.41	24.89
	(0.668)	(0.177)	(0.851)	(0.333)	(0.493)	(0.242)
Difference Hansen test	9.92	17.38	5.68	0.49	0.94	0.15
	(0.701)	(0.250)	(0.957)	(0.486)	(0.333)	(0.935)
AR (1) test (p-statistic)	0.000	0.000	0.000	0.000	0.000	0.000
AR (2) test (p-statistic)	0.141	0.556	0.885	0.771	0.824	0.111
No. of instruments	25	25	25	13	13	24
No. of obs	10,961	6,232	2,279	3,658	11,836	10,756

Note: Significance levels: *p<0.10; **p<0.05; ***p<0.01. Standard errors clustered at the firm level are in parentheses. Variables are winsorized at 1% and 99% level.