Climate policy uncertainty and firms' and investors' behavior*

Pier Basaglia†, Stefano Carattini‡§¶‖, Antoine Dechezleprêtre** and Tobias Kruse**

January 27, 2022

Abstract

Whether and how firms are affected by uncertainty revolving around the implementation of climate policy is crucial to understand their behavior as well as investors', which are interesting per se and also have implications for the potential for systemic risk related with the coordinated implementation of ambitious climate policy. Hence, we develop a new index of climate policy uncertainty, covering the United States with monthly-level variation between 1990 and 2019. We analyze the relationship between climate policy uncertainty and firm-level outcomes such as stock returns, share price volatility, investments in research and development and patenting, and employment for all publicly-listed firms in the country. We find that climate policy uncertainty tends to considerably affect all these outcomes, and often more so than existing indices of economic policy uncertainty. The direction of the effect may, however, be driven by the underlying source of uncertainty, which we measure explicitly. In particular, we leverage the fact that climate policy requires the transition from a "dirty" to a low-carbon equilibrium, with progress and setbacks along the road, which create a promising context to analyze short-term versus long-run planning and belief revision. Consistently with expectations, we find that climate policy uncertainty can lead to positive effects on the abovementioned outcomes in periods of setbacks, i.e. when uncertainty is driven by failure in the climate policy process rather than success.

Keywords Uncertainty; climate policy; firm decision-making; investment; beliefs
JEL codes D22; D83; G10; O32; Q58

*We are grateful to Moritz Drupp, Andreas Lange, Grisha Perino, and Suphi Sen for helpful comments on a previous version of this manuscript. We also thank Sunyoung An, Xiangyu Meng, Miriam Savané, and Shravani Vakkantula for excellent research assistance. Carattini acknowledges support from the Grantham Foundation for the Protection of the Environment through the Grantham Research Institute on Climate Change and the Environment and from the ESRC Centre for Climate Change Economics and Policy as well as from the Swiss National Science Foundation, grant number PZ00P1_180006/1. The usual disclaimer applies.

†Department of Economics, University of Hamburg

‡Department of Economics, Andrew Young School of Policy Studies, Georgia State University

§CESifo

¶Grantham Research Institute on Climate Change and the Environment and ESRC Centre for Climate Change Economics and Policy, London School of Economics and Political Science

‖Department of Economics and SIAW-HSG, University of St. Gallen

**Economics Department and Environment Directorate, Organisation for Economic Co-operation and Development

1 Introduction

Understanding the behavior of agents such as firms and investors is a crucial component of economics, with important implications for society at large. Often, firms' and investors' decisions are analyzed with respect to a change in policy or another aspect that determines the environment in which they operate. However, at least as often firms and investors need to take decisions in a context of substantial uncertainty. Economists have long recognized the role of uncertainty (Bernanke 1983; McDonald and Siegel 1986), but only relatively recently started measuring it in a systematic way (Baker et al. 2016; Hassan et al. 2019).

Climate change is one of the most pressing issues of this century. The need to mitigate climate change has been known among scientists for some four decades and in policy circles at least since the early 1990s. However, recent human history shows that there is much more uncertainty on the implementation of climate policy, domestically and internationally, than there is on climate change itself. Hence, climate change, with its all-encompassing need for change, offers a suitable context to examine behavior by firms and investors under uncertainty. How firms and investors respond to uncertainty related to climate policy also has implications for climate mitigation. In particular, firms' expectations about future climate action may influence their decisions concerning innovation as well as the choice of inputs, in particular labor and capital, which are crucial dimensions for the transition to a cleaner economy. Yet, these dimensions have been examined mostly in response to actual policy changes (e.g. Martin et al. 2014; Aghion et al. 2016; Calel and Dechezleprêtre 2016; Yamazaki 2017).

Further, analyzing firms' and investors' responses to uncertainty in climate policymaking is also informative for the analysis of "transition risk", potential systemic risk driven by the relatively abrupt implementation of ambitious climate policy after decades of delay. With the Paris Agreement, countries committed to reduce greenhouse gas emissions to keep temperature increases within 1.5-2°C above pre-industrial levels. Each signatory pledged to reduce emissions, in absolute terms or relative to a business as usual scenario (Tobin et al. 2018). With the quantity based approach behind the Paris Agreement, pledges set the ambition. Then, policymakers need to identify ways to make sure that a set of instruments is implemented to meet the pledges. Hence, policies systematically trail ambition. One implication that follows from this approach is that firms may be misaligned with long-run climate goals. This misalignment could have, in turn, two main implications: first, firms may continue to invest in "dirty" technologies, leading to continued emissions as well as potential asset stranding and investors' losses once policy risk is materialized (see van der Ploeg and Rezai 2020b for a review); second, if ambitious climate policy is suddenly implemented, possibly in coordination among countries, adjustments in the stock market due to the abovementioned asset stranding could potentially lead to a systemic shock, especially considering that carbon-intensive sectors can represent up to half of an advanced economy's standard portfolio (Battiston et al. 2017; ECB 2021). Many influential voices have raised concerns about systemic risk related to a potentially abrupt transition to a low-carbon economy, including central banks and financial regulators in some of the world's major economies (e.g. Carney 2015; Vermeulen et al. 2018; Banque de France 2019; Rudebusch 2021) Hence, it is of fundamental importance to examine the behavior of firms in presence of uncertainty on the likelihood and timing of future climate policy developments.

How does uncertainty in climate policy affect the behavior of firms and investors? To address this question, we built the first index of policy uncertainty specific to climate policy, which allows us to address this question empirically. Our "climate policy uncertainty" index, or CPU, combines the original search strategy in Baker et al. (2016) with keywords related to climate policy. Our index runs monthly from 1990 to 2019 and covers the main newspapers in the United States. Then, we analyze the relationship between CPU and firm outcomes such as share price volatility and share price, employment decisions, and investments in research and development. Our approach also takes into account a crucial feature related to climate policy. While in the case of standard economic policy the economy tends to move along a given trajectory determined by its steady state and uncertainty tends to be detrimental to economic growth, in the case of climate change the economy needs to transition from fossil fueled activities to a cleaner way of production. Hence, the economy needs to move from one equilibrium, which is carbon intensive, to another equilibrium, which is much cleaner. Since climate change entered the policy arena in the 1980s, both domestic and international climate policymaking have gone through important achievements as well as numerous setbacks. If firms and investors respond to short-term variation in the probability of future policy tightening, rather than adopting long-term goals such as decarbonization, setbacks are likely to benefit them. For this reason, our index is complemented by two sub-indices, aimed at measuring whether the source of uncertainty is an acceleration in the process of decarbonization, or rather a deceleration.

The primary empirical goal of this paper is to examine how economic outcomes respond to greater uncertainty about climate policy, also depending on its drivers. To do so, we exploit variations in our Climate Policy Uncertainty (CPU) index, and its sub-indices, across different months, quarters or years from 1990 to 2018. Specifically, we estimate fixed effects models where we interact our news-based indeces with the average carbon intensity across 4-digit SIC industries. By doing so, we develop an identification strategy that differentiates firms according to their relative exposure to climate policy risk. Using panel data on publicly-listed companies, our model tests whether exposure to climate policy risk matters for economic outcomes when greater uncertainty about climate policy materializes as measured by newspaper article coverage.

Overall, we find that an increase in our index is associated with greater implied stock price volatility and lower share prices, as well as reductions in R&D efforts and annual employment levels. Nevertheless, our results also suggest that the direction of the estimated effects appears to change depending on the underlying drivers of climate policy uncertainty. Finally, further empirical investigations reveal that firm-level economic outcomes are more sensitive to uncertainty about climate policy when changes in expectations point towards more stringent regulation in the future. Our results are robust to a host of sensitivity tests, including the use of an alternative version of our index with a restricted search strategy, a different estimation window that ensures comparability across all our outcome variables as well as a number of different control choices.

We contribute to four strands of literature. First, a growing literature examining the role of policy uncertainty on a wide range of outcomes (Bernanke 1983; McDonald and Siegel 1986; Hassett and Metcalf 1999; Handley and Limão 2015; Baker et al. 2016; Hassan et al. 2019), including investments in green technologies in a set of specific contexts (Fabrizio 2013; Dorsey 2019). We contribute to this literature by introducing an index of climate policy uncertainty, which allows us to examine firms' and investors' responses to changes in the probability of climate policy tightening for the largest firms in the United States over about four decades. Second, a recent theoretical literature on firms' and investors' decisions under the specter of future climate policy (e.g. Rozenberg et al. 2018; van der Ploeg and Rezai 2020a), including implications in terms of systemic risk (e.g. Carattini et al. 2021; Diluiso et al. 2021), and a recent set of empirical applications testing the theory (e.g. Carattini and Sen 2019; Sen and von Schickfus 2020; Engle et al. 2020; Krueger et al. 2020). We contribute to this literature by providing additional empirical evidence on a range of firm-level outcomes from shocks in climate policy uncertainty. Third, a stream of research examining the role of innovation in response to environmental regulation, analyzing, theoretically and empirically, the role of directed technical change (e.g. Bovenberg and Smulders 1995; Porter and van der Linde 1995; Popp 2002; Acemoglu et al. 2012; Aghion et al. 2016; Calel and Dechezleprêtre 2016; see also Ambec et al. 2013 for a review). Unlike the existing literature, which infers mostly from existing policies, leveraging changes in stringency, our study focuses on variations in uncertainty, leading to adjustments in firm's beliefs about the likelihood of future policy tightening or weakening. Fourth, an empirical literature showing relatively muted changes in employment following tightening in environmental regulation (Martin et al. 2014; Yamazaki 2017). Also in this case, we contribute to the literature by covering changes in uncertainty about potential regulatory changes, rather than only realized policy shocks, and uncovering their effects on employment levels over a long period for a large number of firms.

The paper proceeds as follows. Section 2 introduces our CPU index as well as its sub-indices. Section 3 describes the data and empirical approach. Section 4 presents our empirical results. Section 5 concludes.

2 Introducing the CPU index

2.1 Building the index

This study builds upon the work of Baker et al. (2016) in order to develop an indicator of climate policy uncertainty using a comparable methodological approach, which we detail in what follows.

To build their index of Economic Policy Uncertainty in the U.S., Baker et al. (2016) count the frequency of newspaper articles that contain the following trio of terms: (1) "economic" or "economy"; (2) "uncertain" or "uncertainty"; and (3) "Congress", "deficit", "Federal Reserve", "legislation", "regulation" or "White House". To build our index of Climate Policy Uncertainty (CPU), we similarly created a lexicon of words and combinations of words as our search strategy. To ensure that we capture the right concept, we create a separate lexicon of words for each of the three components (Climate, Policy, and Uncertainty). The first category includes terms such as "pollution", "CO2", or "climate change" which refer to a specific concern related to climate change. It also includes terms referring to technologies addressing these concern such as "solar PV" or "renewable". The second category includes terms related to policy making such as "regulation", "legislation", or "tax", but also terms more specific to environmental policies such as "emissions trading scheme" or "cap and trade". The full list of keywords used in these two components are listed in Appendix A. The third category includes the words "uncertain" or "uncertainty". Selected articles have to include at least one term from each category.

We initially created the lexicon in English in order to capture articles in English-speaking countries. All keywords were then translated, by native speakers, in several other languages. Appendix A provides the keyword selection for all languages.[1] In this paper, we use the English version, applied to the United States.

The main challenge in creating an indicator of policy uncertainty based on counts

[1] To ensure that our index is consistently observed across countries, we avoid using country-specific terms. For example we do not include the exact name of environmental ministries, departments, or environmental protection agencies. The names of ministries or departments dealing with environment and climate change topics tend to change with governments, which make them difficult to track consistently across countries and time. In the United Kingdom, for instance, the Department for Energy and Climate Change became part of the Department for Business, Energy & Industrial Strategy in July 2016 following a change in government.

of newspaper articles is the possible inclusion of "false positives", which are articles that are not relevant but are still selected based on the search strategy. Such false positive results would inflate our index and incorrectly indicate higher levels of uncertainty. In turn, they would introduce downward bias in the empirical analyses. To reduce as much as possible the likelihood of including such false positives, we read several hundreds of randomly selected articles and recursively adjusted the search strategy. We manually coded the randomly selected articles as relevant and irrelevant. We were thereby able to adjust the search strategy systematically to increase the ratio of relevant articles to above 80%, which is considered as a reasonable compromise between including as many relevant articles as possible and limiting the extent of false positives.

To ensure that the selected articles talk about climate policy and not about climate in one part and about unrelated policies in another, we imposed the restriction that terms from the policy category have to be located within the same paragraph from the respective word in the climate category. We thereby contribute to ensure that the two terms are related to each other in the newspaper article. A difficulty when using terms such as "environment" or "climate" is that they can also be used to describe other concepts such as "business climate", "business environment" or "policy environment". We therefore explicitly excluded all articles that used one of these expressions. An additional challenge in creating topic-specific policy uncertainty indices is that they tend to require many more search terms compared to general economic policy uncertainty indicators. This is necessary to ensure that as many topic-related events as possible are picked up. Baker et al. (2016) are able to obtain a comprehensive coverage of economic policy uncertainty with ten search terms for the United States. For our climate policy uncertainty index, we apply more than 60 search terms. Since newspaper coverage of climate-related policy uncertainty is typically smaller than coverage of economic policy uncertainty, our search strategy needs to be sufficiently sensitive in order to observe as many topic-specific events as possible.

For the United States, the CPU index covers the years from 1990 until 2019. The main reason to start the index in 1990 is that, prior to that date, the number of available newspaper articles is smaller, and potentially too small. However, in some of our analyses we also consider the period from 1980 to 2019, as this extension of the index allows to determine how investors' and managers' beliefs were first revised when climate change entered the policy arena, and further adjusted when it became evident that cooperation on international climate policy would have been rather hard to achieve. For all remaining countries considered in this study, the index goes further back in time in accordance with the respective data availability.

To construct their indicator of economic policy uncertainty for the United States, Baker et al. (2016) use data from 10 leading newspapers. Limiting the search to leading newspapers ensures the quality of the underlying articles and avoid including newspapers that only exceptionally report on the topic, spuriously creating huge volatility over time. Here, we focus on the *New York Times*, the *Washington Post*, and the *Wall Street Journal*. We similarly select a set of major newspapers for each country, as documented in Table 1. The number of newspapers varies slightly across countries, depending on the characteristics of national newspaper markets, as well as on data availability.

Table 1: Newspaper sources by country

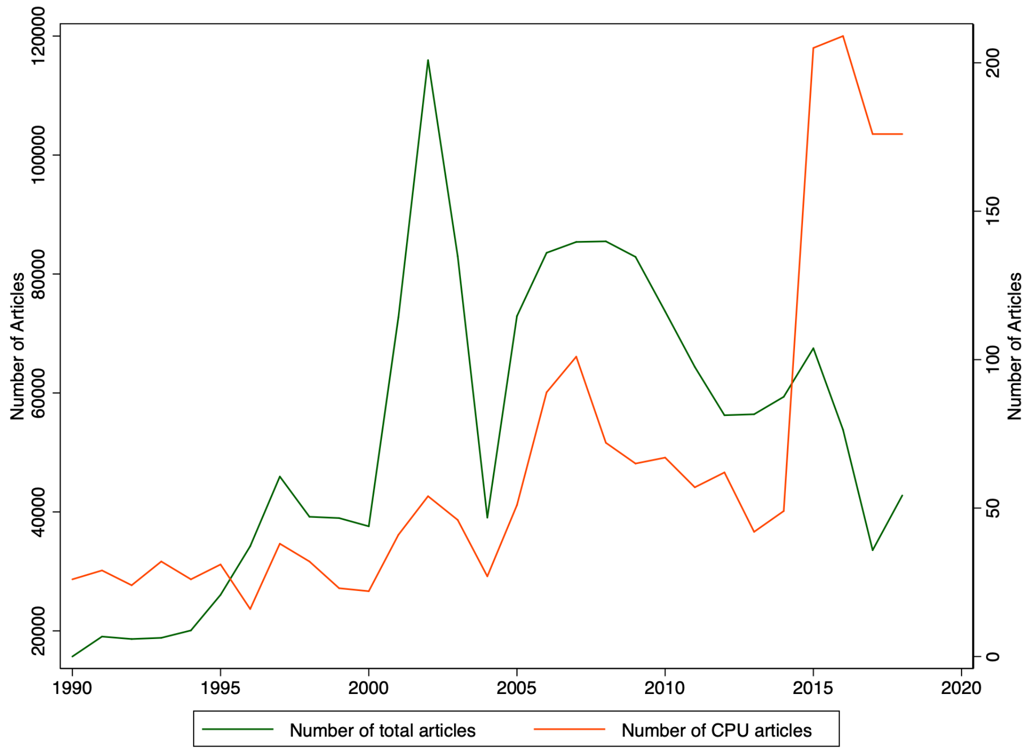
Country	Newspapers covered in CPU index
United States	*The New York Times*, *The Washington Post*, *The Wall Street Journal*
United Kingdom	*The Financial Times, The Independent*, *The Telegraph*, *The Guardian, The Times*
Canada	*The Globe and Mail*, *Toronto Star*, *National Post*, *The Calgary Herald*,
	Ottawa Citizen, *Montreal Gazette*
Australia	*The Age, The Australian, The Australian Financial Review, the Sydney Morning Herald*
France	*La Tribune*, *Le Figaro*, *Le Figaro Economie*, *Le Monde*, *Les Echos*
Germany	*Die Süddeutsche Zeitung*, *Die Welt*

For each newspaper, we separately downloaded the annual count of articles that are picked up by our search strategy as well as the total number of articles published by the outlet. Two online newspaper databases were used to download the article counts, Factiva and Nexis, covering different sets of newspapers. As an illustration, Figure 1 shows the annual article counts for the *New York Times* (United States) and, for comparison, Figure 2 shows the annual article counts for *The Guardian* (United Kingdom). These time series show the trends in overall articles (left axis) and in articles on climate policy uncertainty (right axis). The number of annual articles related to climate policy uncertainty varies between 0 and 300, with significant year-on-year variation. Overall, the frequency of articles on climate policy uncertainty appears to have increased in the recent period, but the total number of articles published has increased as well.

Figure 1: Article counts in the *New York Times* (US)

Note: Yearly series from 1990 to 2018.
Source: Factiva.

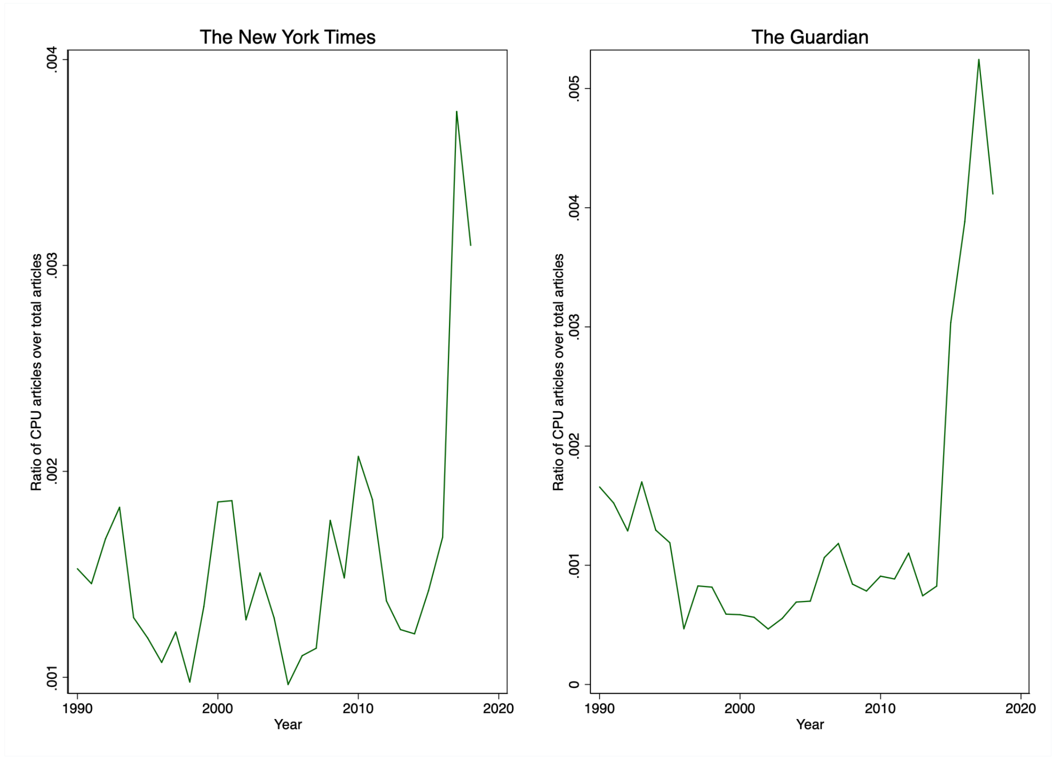
Figure 2: Article counts in the *Guardian* (UK)



Note: Yearly series from 1990 to 2018.
Source: Factiva.

In order to account for this rising trend in total articles published, we first compute a simple newspaper-specific ratio of articles on climate policy uncertainty over the total article count by newspaper. This ratio is displayed in Figure 3 for the same newspapers of Figures 1 and 2. Over time, less than 2 in 1000 articles deal with climate policy uncertainty in the *New York Times*, further justifying our choice to use multiple keywords to cast as wide a net as possible given the specificity of the topic of interest in the general press. Figure 3 shows, however, that this ratio varies significantly over time and differently so across newspapers: while the proportion of articles mentioning uncertainty related to climate policy has increased markedly since 2016 across both newspapers, the recent increase in the *New York Times* follows a number of more pronounced earlier peaks. These differences may reflect domestic dynamics, which we will further discuss below.

Figure 3: Ratio of Climate Policy Uncertainty articles over total articles

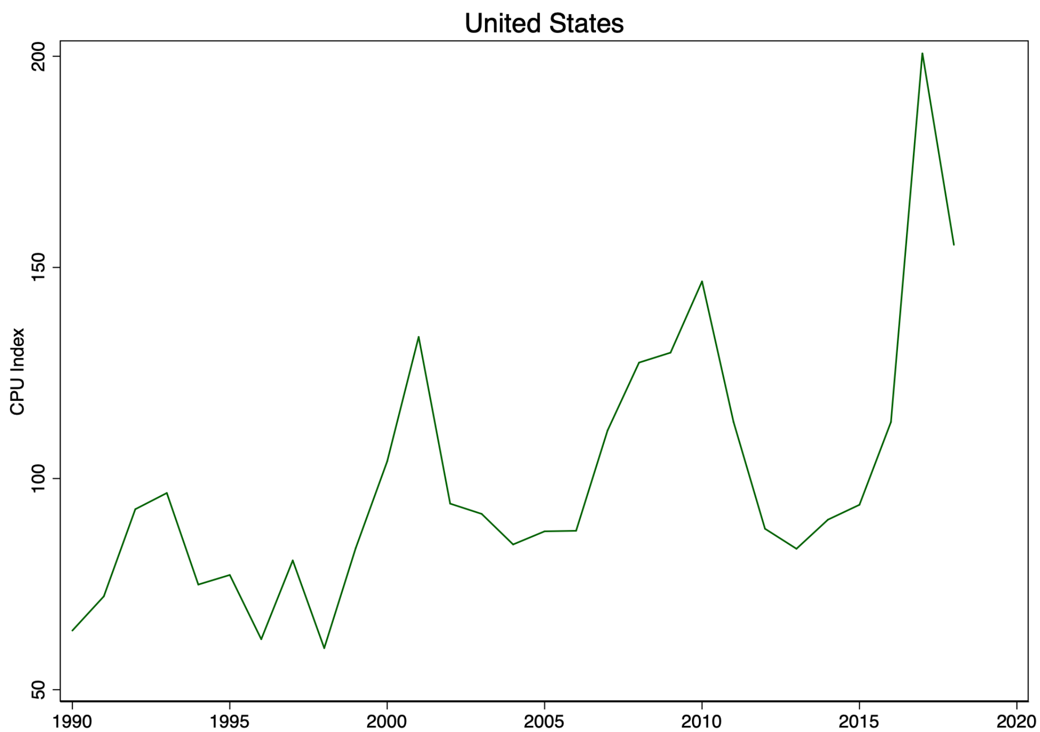


Note: Based on yearly series from 1990 to 2018.
Source: Factiva.

A challenge with these raw article ratios is that the number of articles varies a lot across newspapers and time, making it difficult to simply average the ratios across several newspapers in a given country. We therefore apply the standardization approach of Baker et al. (2016) to obtain our CPU index. We begin with the simple ratio of articles on climate policy uncertainty divided by the total article counts for each newspaper, as illustrated in Figure 3. For each newspaper we then divide this ratio by the newspaper-specific standard deviation across all years. This creates a newspaper-specific time series with unit standard deviation across the entire time interval, which ensures that volatility of the overall country-level index is not driven by a higher volatility of a particular newspaper. We then average these standardized series across all newspapers within each country by year. Lastly, we normalize the country-specific series to a mean of 100 over the time interval.

Figure 4 shows the resulting index over the time period 1990 to 2018 for the United States. Figure C.1 in Appendix C covers 5 additional selected countries: Australia, Canada, France, and Germany.

Figure 4: CPU index in the United States

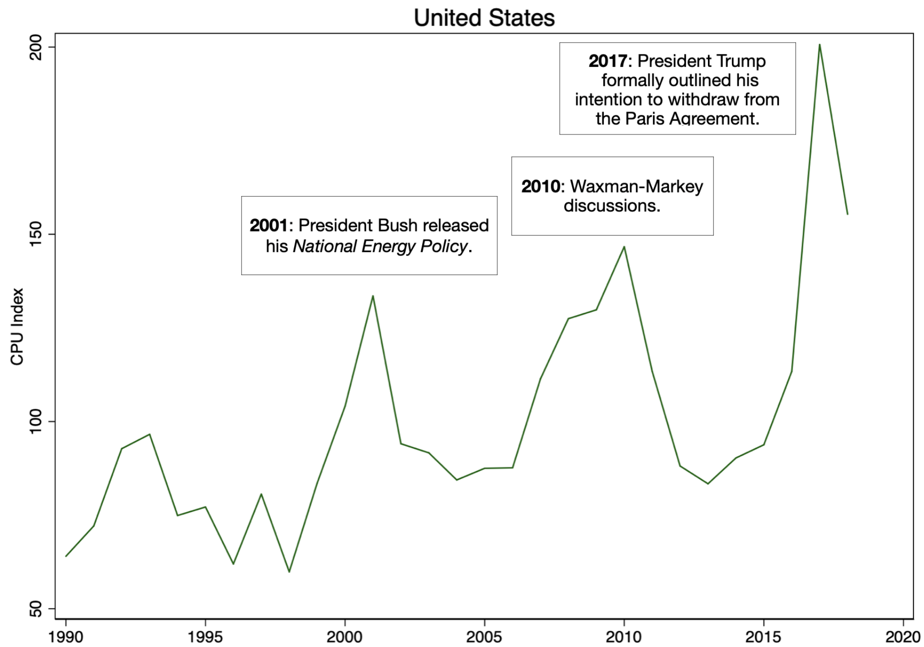


Note: Based on yearly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

2.2 Validating the index

As a first approach to validate our index, and following Baker et al. (2016), we link the country-specific peaks to relevant events such as the discussion or implementation of major climate policies. To verify that our index varies in conjunction with the respective events and the corresponding realization of uncertainty, we read the headlines of the first hundred articles that were downloaded for the peak years. In the United States, the index has pronounced peaks in 2001, 2010, and 2017, as shown in Figure 5. The first peak in 2001 is linked to the Energy Plan published by the George W. Bush administration that included environmental deregulation, in particular with respect to oil and gas explorations. While the event itself created climate policy uncertainty by lowering environmental standards, the lengthy discussion around the publication of the plan also contributed to the spike of the index. The spike in 2010 is driven by the Democratic party withdrawing a major bill on climate change due to insufficient support in Congress. Moreover, the prior discussion on whether the bill might achieve sufficient support in Congress and whether the Democratic party might be willing to amend the bill contributed to the uncertainty. The third spike in 2017 is in turn related to uncertainty arising from President Trump's withdrawal from the Paris Agreement and efforts to revoke clean energy and climate policies. Appendix B.1 provides an extended list of major events in the United States relevant for climate policy uncertainty, which we leverage later in this section as well as in the remainder of the paper. Visibly, such major events relate to both instances of progress as well as setbacks in dealing with climate change, supporting the generation of sub-indices, as described in the next section, capturing these two forces, respectively. The corresponding figures for the array of countries covered in our study are included in Appendix C.

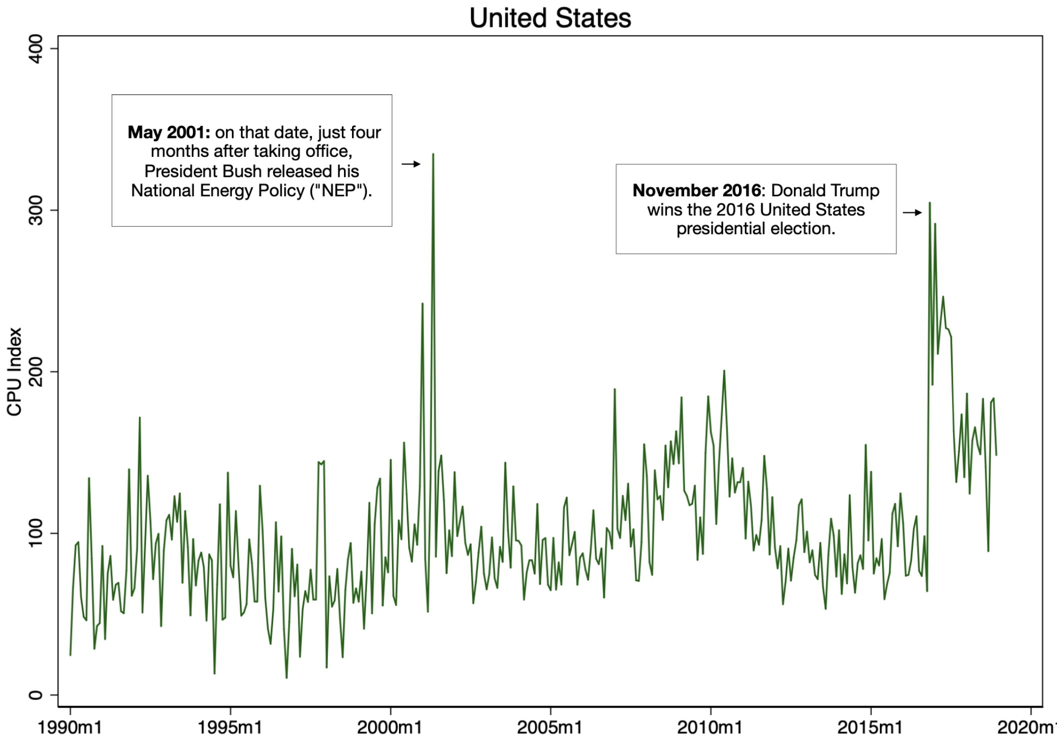
Figure 5: CPU index and associated events in the United States



Note: Based on yearly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

In addition to the annual time series of the CPU index, we are also able to establish a monthly index for the United States, where the annual number of articles related to climate policy uncertainty is high enough to be further disaggregated. This more granular data allows us to examine the variation in the index in more detail, which we do in Figure 6, as well as to analyze responses by high-frequency variables such as stock market values and volatility to climate policy uncertainty shocks, which we do in the following sections, among other outcome variables, using either monthly or quarterly series.

Figure 6: Monthly CPU index in the United States



Note: Based on monthly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

Based on a careful analysis of the newspaper article headlines and abstracts we are again able to link the peaks to particular policy events and their corresponding realization of uncertainty. Interestingly, we observe a trend in the topics of climate policy uncertainty moving from energy-related issues largely concerned with energy security and energy prices in the 1990s and early 2000s to increasing attention explicitly given to air pollution and climate change issues from the late 2000s onwards. The early events include the uncertainty around energy prices following Iraq's invasion of Kuwait as well as the abovementioned discussion around the Energy Plan of the George W. Bush administration in 2001 that included deregulation in particular for oil and gas exploration. The later events include in particular uncertainty arising around the discussion and abrupt withdrawal of a bill to regulate ozone emissions in September 2011 under the Obama administration as well as the election of President Trump, who then announced a planned withdrawal of the United States from the agreement.

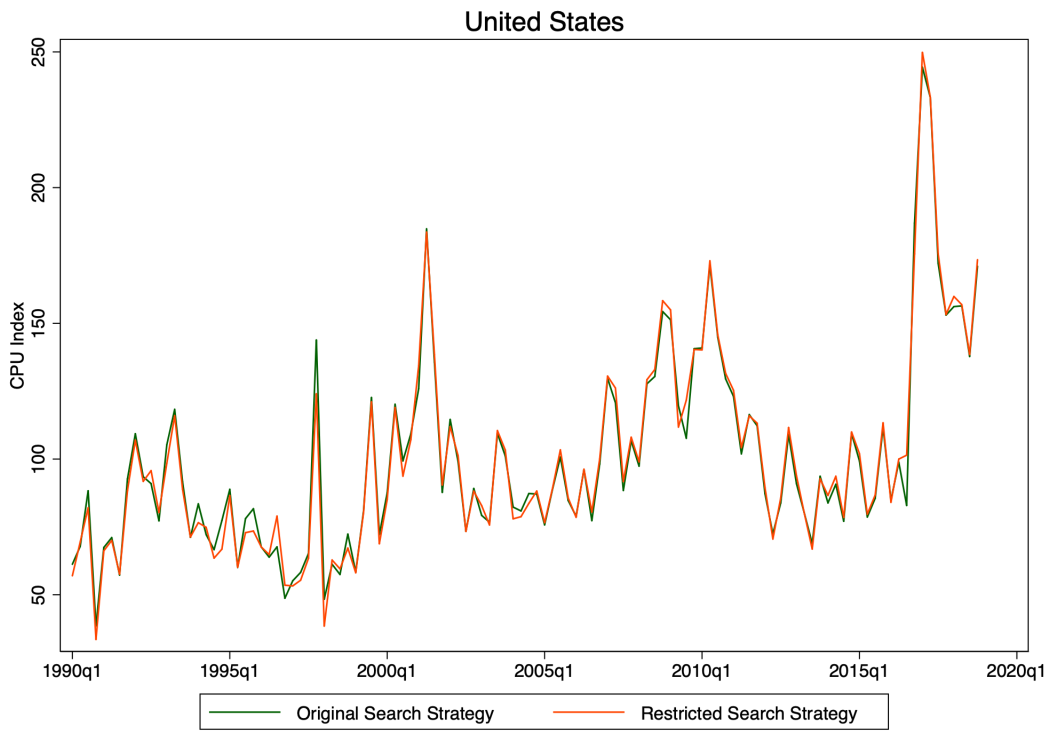
It is, however, important to note that, by design, annual (Figure 5) and monthly (Figure 6) time series can identify different peaks. Such difference can arise if, for instance, the discussion of a policy change spreads across many months within a single year. The frequency per month may be relatively low, but if all the articles are aggregated within a year, they can lead to a peak in the annual time series. In the United States, this occurred for instance with the 2010 withdrawal of the climate change bill under the Obama administration. While it appears as a spike in the yearly chart, the spike in the monthly series is less marked. Figure 6 shows elevated levels of climate policy uncertainty throughout 2010. The withdrawal of the bill was not a major surprise as it had already appeared that the administration did not have sufficient support in Congress to see it pass. Therefore, the combination of both annual and monthly time series provides unique insights as it allows us to examine all policy events from both perspectives.

Section E further compares the index to other relevant measures, such as the EPU from Baker et al. (2016), the Chicago Board Options Exchange's CBOE Volatility Index (hereafter referred to as VIX), and oil price volatility.

2.3 Extending the index

We provide two extensions to the index, which are documented in more detail, including the keyword searches, in Appendix A. First of all, since our baseline search strategy includes keywords potentially relating to local air pollution, we run a new newspaper article search that excludes them. Figure 7 plots the evolution of the two indices since 1990: Overall, they exhibit a correlation of 0.9923. The index resulting from the narrower search, which we denote as N-CPU for Narrow Climate Policy Uncertainty, will be used for robustness tests in Section 4.2.

Figure 7: Comparing the evolution of the CPU and N-CPU indices



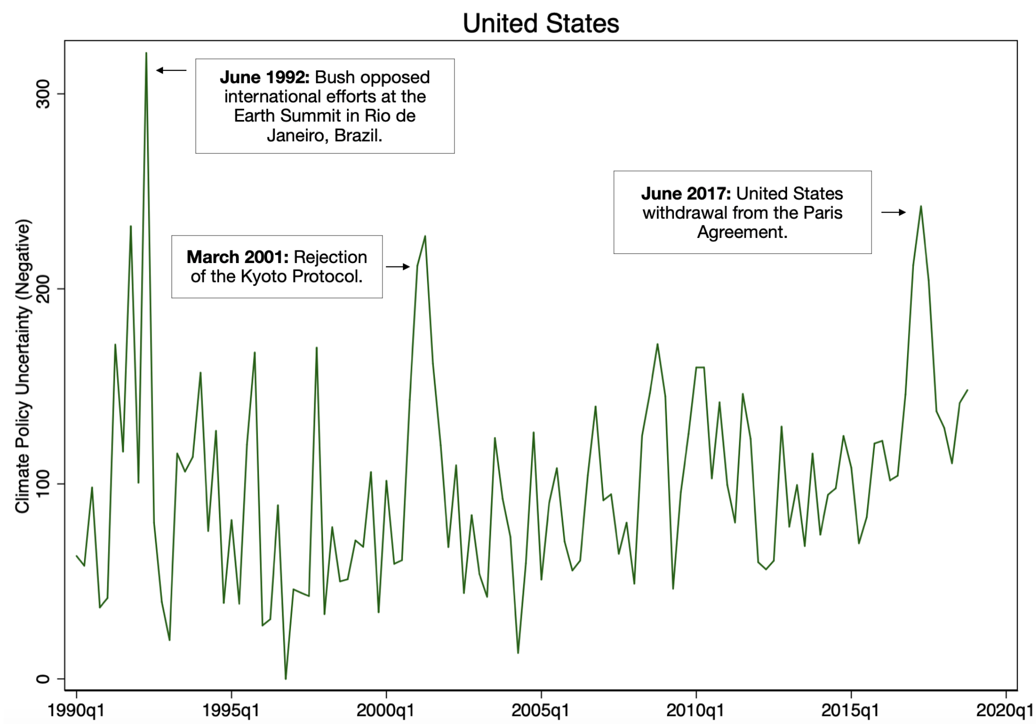
Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

The second extension follows from an important observation about the difference between our CPU index and the EPU index developed by Baker et al. (2016). While in the case of standard economic uncertainty, any increase in the index, and thus in the underlying uncertainty, is overall detrimental for economic output, the case of climate policy uncertainty is very different. The EPU index largely measures the effect of uncertainty as a destabilizing factor from a trajectory of economic growth.

In contrast, the CPU index measures the uncertainty surrounding the pace at which the economy is expected to move from business as usual to carbon neutrality. In this context, there is a trade-off between economic output and climate change mitigation, so that an increase in climate policy uncertainty has two effects: first, a negative shock on economic output due to the direct effect of uncertainty, as analyzed by Baker et al. (2016); second, an effect that depends on how beliefs on the pace of the transition towards a cleaner economy are adjusted. Indeed, the process of implementing climate policy, both domestically and internationally, has had many instances of acceleration and deceleration. While when climate change entered the political arena in the '80s expectations might have been that of a relatively quick transition to less fossil fuels, as recommended by scientists, it later became apparent that (international) climate change mitigation would have been harder to achieve than coordination in banning products responsible for ozone depletion as done with the Montreal Protocol. In more recent times, however, unilateral initiatives, followed by the Paris Agreement, and the emergence of a new generation of environmental leaders, have pointed to an acceleration in climate change mitigation. Over only a few years, carbon pricing went from covering 15% of global emissions to about 22.5% (World Bank 2020). Unless investors are aligned with long term climate goals as provided by climate scientists and unmoved by present political developments, which do not seem the be the case (see e.g. Carattini and Sen 2019), we would expect stock markets to make gains when new developments point to additional delays in climate action and to make losses, everything else equal, when new developments point to an acceleration in climate action.

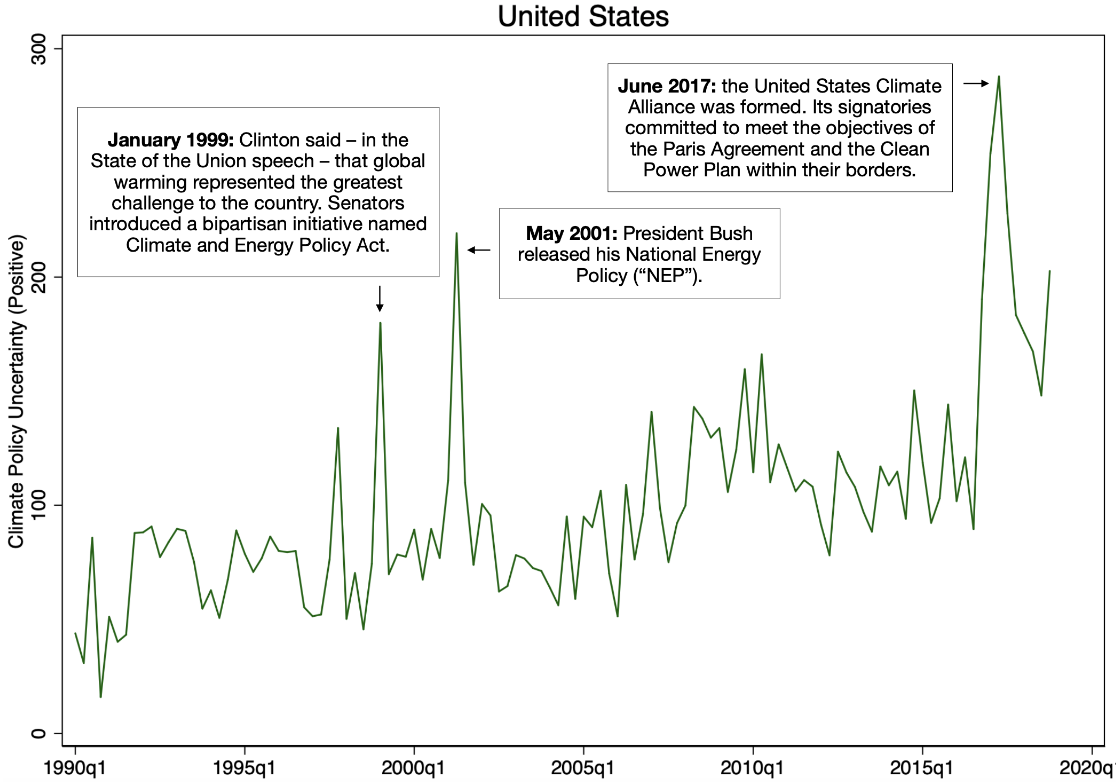
Hence, it is important not only to analyze variation in the CPU index but also try to disentangle its drivers, whether an increase in uncertainty suggests that the transition is slowing or accelerating. To this end, we performed two additional separate searches, adding keywords related to progress and failure, respectively, to the standard keyword search. We denote the resulting sub-indices as O-CPU when belief revision goes towards more climate action (hence the "O" stands for optimism) and P-CPU when belief revision goes towards less climate action (hence the "P" stands for pessimism). Figures 8 and 9 plot the evolution of the sub-indices over time, linking respective index-specific peaks to policy-relevant events.

Figure 8: Quarterly P-CPU index in the United States



Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

Figure 9: Quarterly O-CPU index in the United States



Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

3 Data and empirical strategy

3.1 Data and descriptive statistics

To examine whether climate policy uncertainty has an impact on economic outcomes, we combine several data sources on publicly listed firms. In particular, we investigate firms and investors' responses to uncertainty about climate policy by focusing on share prices and volatility, research and development (R&D) expenses, and employment. All variables except volatility are obtained from Standard & Poor's Compustat, specifically from Compustat North America, which includes information for companies listed in the United States and Canada. Additionally, we combine information retrieved from Options Metrics, which provides volatility implied by firm-level equity options over different time horizons since the mid-1990s in our main estimations, as well as longer time horizon in alternative specifications. Table 2 is based on firm-level information for publicly-listed companies in the US between 1990 and 2018.

3.1.1 Outcome variables

We use daily data on volatility from Option Metrics' implied volatility which provides historical information on 30-day volatility implied by firm-level equity options. We include in our dataset all options that have been traded on the Chicago Board of Options and Exchange since 1996.[2] We consider option-implied share price volatility as a proxy for firm-level uncertainty. We then combine information on share prices, research and development (R&D) expenses, and employment for the entire universe of publicly traded firms in the United States since 1990. For instance, our analysis with share price as outcome variable covers arond 10,000 listed companies in the United States. Share prices refer to a stock's closing price, which is the standard benchmark used by investors to track its performance in time. Compustat North America provides information on share prices since 1962, which allows us to analyze the relationship between this outcome variable and the index since 1980. R&D expenses are included in the sample to proxy firm-level innovative behavior. These expenses are defined as the costs incurred throughout a given quarter that cover the development of new products or services. Information on R&D expenses is only available since 1989. Finally, employment refers to the annual level of employees in a given company since 1980.

[2] As information on stock-price volatilities is only available from 1996, we check whether our results change when running our estimations for other outcome variables from 1996 onward.

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Median
Volatility (30)	298103	-1.042	.637	-6.398	2.47	-1.043
Share Price	1433855	.87	3.247	-13.816	13.423	2.053
R&D	288375	.768	2.324	-6.908	9.299	.761
Employment (Annual)	220356	8.692	38.375	0	2545.209	.574

Notes: Table shows summary statistics for publicly-listed companies in the US between the years 1990-2018 without sample restrictions. Variables are expressed in log-terms.

3.1.2 Emission intensities

Further, we are interested in analyzing whether the abovementioned economic outcomes are differentially affected based on the exposure to climate policy risk of each firm, which we proxy by emission intensity. To this end, we combine information on emissions from the US Environmental Protection Agency (EPA). The EPA tracks facility-level emissions of air pollutants, through the Greenhouse Gas Reporting Program (GHGRP). The GHGRP collects annual information on the emissions of different greenhouse gases, primarily on carbon dioxide (CO_2).[3] The reporting program provides data on individual facilities, thus offering an opportunity to disaggregate nationwide emissions' estimates to narrowly-defined industries or specific companies. The database covers approximately 85% to 90% of total greenhouse gas emissions in the United States from 2010 to 2018.[4] This includes data on direct emissions reported

[3] Carbon dioxide is the greenhouse gas (GHG) emitted in the largest quantities: carbon dioxide emissions reported in 2018 represented 90.9% of the total emissions of GHGs reported during the year. Other greenhouse gases covered include methane (CH_4), nitrous oxide (N_2O) and fluorinated GHGs (HFCs, PFCs, SF_6). In 2018, methane emissions represent 7.6% of total GHG emissions, N_2O represented around 1.0%, and fluorinated gases accounted for around 0.5% (see https://www.epa.gov/sites/production/files/2019-10/documents/ry18_ghgrp_yearly_overview.pdf, last accessed on September 20, 2020).

[4] There are a specific thresholds above which reporting is required within a given industry. In general, the threshold is set at $\geq$ 25,000 metric tons CO_2-e per year. Conversely, all facilities in the following industry categories must report regardless of annual

by stationary sources, covering nearly all direct emissions from electricity generation and most emissions from industry, which account for approximately 50% of total nationwide emissions. In addition, this also includes GHG data reported by suppliers of fossil fuels and industrial gases, which account for the vast majority of emissions from transportation, commercial, and residential sources, representing roughly 40% of total US emissions. The GHGRP does not include emissions from the agriculture and land use sectors, or other small sources of emissions.

Our main model specifications differentiate firms by their relative exposure to climate policy changes. The underlying intuition is that more pollution-intensive firms would be more exposed to the possibility of more stringent climate regulation in the future. To compute this exposure, we draw on facility-level information on air emissions from the GHGRP. As a first step, we match Compustat firms to reporting facilities using the names of their parent companies, which is provided by the EPA. We do so using Standard & Poor Capital IQ's Identifier Converter which allows to identify company identifiers of all public firms using company names. The GHGRP database includes detailed ownership percentages of facilities by multiple parents, and we rely on these values to assign each facility's pollution to its parent companies. Through this match, we yield parent firms' annual levels of carbon dioxide emissions, which we use to obtain firm-level intensities as the ratio of total air emissions to total revenue. We then aggregate emission intensity levels to obtain the ratio of air emissions to revenues in each four-digit industry by year. Finally, we average these ratios to compute our exposure measure for each four-digit SIC industry. Table 3

emissions: Electricity Generation, Petroleum Refineries, Adipic Acid Production, Ammonia Manufacturing, HCFC-22 Production from HFC-23 Destruction, Nitric Acid Production, Petrochemical Production, Phosphoric Acid Production, Silicon Carbide Production, Titanium Dioxide Production, Aluminum Production, Cement Production, Lime Manufacturing, Soda Ash Production.More information on reporting requirements by industry can be found here: https://ccdsupport.com/confluence/pages/viewpage.action?pageId=93290546. Last accessed on September 6, 2020.

displays intensity by 4-digit SIC code averaged across main industry group classifications. Nevertheless, there is substantial variation in average carbon intensity across 4-digit SIC codes within industry groups. For instance, carbon intensity in manufacturing ranges from relatively low values in the food industry to much higher levels for manufacturing of cement and metal products. Specifically, Cookies & Crackers (SIC 2052) exhibits an average intensity of around 0.6 metric tons of carbon emissions per million of revenue generated compared to 3310 and almost 4300 metric tons and per million in Cement, Hydraulic (SIC 3241) and Fabricated Metal Products (SIC 3490) respectively. Similarly, intensity values in Services range from 0.09 metric tons/million in Life Insurance (SIC 6311) to 4000 metric tons/million in Oil Royalty Traders (SIC 6792). Appendix D provides the corresponding intensity figures for a number of other selected industries.

Table 3: Average carbon intensity by SIC code

Industry Description	**Range of 4-digit SIC Codes**	**Average Intensity**
Mining	1000-1499	9.92
Construction	1500-1799	9.27
Manufacturing	2000-3999	8.52
Transport, Communications, Electric, Gas and Sanitary Service	4000-4999	9.11
Wholesale and Retail Trade	5000-5999	8.79
Finance, Insurance and Real Estate	6000-6799	8.97
Services	7000-8999	7.61
Median Sample Intensity		9.34

Notes: Industry-level intensities are expressed as natural logs and averaged across SIC codes. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Carbon intensity was computed as the ratio of total air emissions. Carbon intensities are measured in myriagrams CO_2-e to total revenue (in millions of dollars).

3.2 Empirical strategy

The main empirical goal of this paper is to examine how economic outcomes respond to greater uncertainty about climate policy, also depending on its drivers. To do so, we exploit variations in the Climate Policy Uncertainty (CPU) index across different months, quarters or years from 1990 to 2018. Our empirical strategy consists in estimating fixed effects models where we interact our news-based index with the measure of exposure to climate policy risk described in Section 3.1.2. This additional source of variation allows to control for unobserved time-varying confounders. These specifications test whether effects for firms with greater exposure to climate policy shocks covary more strongly with our index. In other words, the model tests whether exposure to climate policy risk matters for economic outcomes when greater uncertainty about climate policy materializes in the news. We estimate the following equation:

$$y_{it} = \beta_1 CPU_t \ x \ Exp_j + \beta_2 X^{'}_{jt} + \gamma_i + \delta_t + \epsilon_{ijt} \tag{1}$$

where y_{it} represents one of the outcome variables presented in Section 3.1.1 CPU_t refers to our Climate Policy Uncertainty index in a given time period t, whereas Exp_j refers to our intensity measures computed for each 4-digit SIC industry, j. ϵ_{it} is the idiosyncratic error term. The main identifying assumption in the model is that companies operating in high-emitting sectors tend to be more exposed to climate policy uncertainty. One potential threat to identification are firm and time-specific shocks. By including firm-specific fixed effects, γ_i, and time fixed effects, δ_{jt}, we are able to capture time-constant firm-specific factors as well as absorb unobserved time-varying shocks. Without the interaction term, CPU_t is collinear with the time fixed effects and drops out from the equation.

Furthermore, we include a vector of controls, $X^{'}_{jt}$, to evaluate to what extent our CPU measure tells us anything different from other measures of uncertainty and policy uncertainty. First, the most obvious choice is to control for variations in the Economic Policy Uncertainty (EPU) index developed by Baker et al. (2016). By doing so, we can assess whether our climate policy uncertainty index can be significant predictor of firm-level economic outcomes after controlling for the impacts of economic policy uncertainty. Both indices are constructed using scaled frequency counts of newspaper articles, but they differ conceptually. While, the EPU index is designed to measure policy-related uncertainty for the economy as a whole, our CPU index quantifies uncertainty specifically related to climate policy. Drawing on Baker et al. (2016), we interact log(EPU) with SIC-specific contract intensity. The latter reflects the average ratio of federal purchases to revenues in each four-digit industry and captures exposure to uncertainty about government purchases. The intuition is that the effects of economic policy uncertainty tend to be more sizable in industries disproportionately relying on direct sales of goods and services to the federal government. Secondly, we test whether our results change when controlling for overall economic uncertainty, approximated by the VIX index - a common measure of expectations of further stock market volatility computed as the 30-day option-implied volatility in the S&P500 index. Even in this case, we interact log(VIX) with SIC-specific contract intensity to differentiate firms by their exposure to overall uncertainty. Finally, we additionally control for fluctuations in the price of oil proxied by the West Texas Intermediate (WTI). This is because persistent spikes in oil prices may also ultimately affect the performance and thus the valuation of companies largely relying on carbon-intensive production processes.

4 Empirical results

4.1 Firm and investor behavior in response to uncertainty shock

We are interested in firms and investors' responses to uncertainty along the following outcome variables: share prices and volatility, research and development expenses, and employment. In our empirical analyses, we focus first on our main index and analyze its relationship for our main outcomes of interest. Then, we test the robustness of our main findings to a host of sensitivity tests. Lastly, we analyze belief revision, leveraging the sub-indices defined as O-CPU and P-CPU.

We now describe the analyses using our main index. We start with share prices and share price volatility. Table 4 displays results from regressing firms' 30-day implied stock price volatility and share prices on climate policy uncertainty. Our estimates of interest are reported in the first row, with robust standard errors clustered at the firm-level. Taking advantage of the high-frequency nature of stock market variables, we provide estimates using both monthly and quarterly time series of our index. Both levels of aggregation provides unique perspectives into the evolution of climate policy uncertainty and contribute to provide a more complete picture for our empirical analysis (see section 2.2). While the quarterly time series provide insights on the effects of enduring uncertainty across months, the monthly series allows to investigate prompt responses to uncertainty shocks occurring within shorter time frames. In our regressions, we use 30-day volatility implied by firm-level equity options. We calculate the average implied volatility over all trading days in a given month or quarter to match stock market data. Our sample extends from 1990 to 2018, as most of our outcome variables are consitently available from 1990 onward only (as described in

Section 3.1.1). However, recall that information on stock price volatility is available from 1996 onward only. Hence, in Appendix F we analyze all outcome variables using 1996 to 2018 as estimation window.

Tables 4 and 5 report results from our monthly and quarterly-level specifications respectively. Overall, our monthly-level estimates indicate that an increase in our index is associated with greater implied stock price volatility and lower share prices. Specifically, we find that for a firm with median exposure, a 1% increase in CPU over a given month leads to an increase of around 0.05% in implied volatility ($\approx$0.0055 x 9.34 = 0.047) and a reduction of 0.09% in share price ($\approx$0.01 x 9.34 = 0.09). In line with our expectations, we observe that firms operating in more carbon intensive 4-digit SIC industries tend to respond more strongly to variations in climate policy uncertainty. Table 5 show how these estimates change when turning to our quarterly-level specifications. Overall, both specifications yield similar results, but the magnitude of the estimated relationships is larger with quarterly series. To assess these magnitudes, our quarterly-level coefficients now predict for a firm with median exposure that a 1% increase in CPU would lead to an increase of 0.08% in implied volatility and a reduction of 0.3% in share price. These results reveal that stock market performances tend to be more sensitive to spikes in climate policy uncertainty when the latter persists over subsequent months. Table F.1 in Appendix F extends our approach to annual series. Even in this case, results suggest that the more persistent the shock, the larger the effect. Furthermore, to put our coefficients into perspective, the quarterly CPU index rose on average by 40.5 log points from 2000 to 2018. Assuming a median exposure, this implies an estimated upward shift in implied volatility of approximately 3% (0.405 x $\approx$0.00816 x 9.34 x 100) and an overall decrease of around 13% (0.405 x $\approx$0.0334 x 9.34 x 100) in share prices attributed to variation in the CPU. Nevertheless, the estimated relationships between fluctuations in the CPU index and stock market variables vary considerably in relation to industry-level carbon intensity.Tables D.1 and D.2 in Appendix D compute the implied changes in implied volatility and share prices from 2000 to 2018 across different industries to explore heterogeneity across firms more in detail.

Table 4: **Effects of climate policy uncertainty on option-implied stock price volatility (30-day horizon) and share prices in the US (monthly series).**

		Volatility (30)			**Share Price**	
	(1)	(2)	(3)	(1)	(2)	(3)
CPU x CO2 intensity	0.00571***	0.00565***	0.00509***	-0.0124**	-0.0121**	-0.00998***
	(0.00159)	(0.00159)	(0.00141)	(0.00484)	(0.00483)	(0.00352)
VIX x Contract Intensity	0.124			-0.511*		
	(0.0986)			(0.269)		
EPU x Contract Intensity		-0.0540	-0.0407		0.512	0.473
		(0.137)	(0.137)		(0.385)	(0.384)
WTI x CO2 intensity			0.00338			-0.00996
			(0.00280)			(0.00972)
Sample	Continuous	Continuous	Continuous	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	273367	273367	273367	956480	956480	956480
R-squared	0.642	0.642	0.642	0.815	0.815	0.815
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	3237	3237	3237	8775	8775	8775
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Month	Month	Month	Month	Month	Month
First Year	1996	1996	1996	1990	1990	1990
Last Year	2018	2018	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 5: **Effects of climate policy uncertainty on option-implied stock price volatility (30-day horizon) and share prices in the US (quarterly series).**

	Volatility (30)			**Share Price**		
	(1)	(2)	(3)	(1)	(2)	(3)
CPU x CO2 intensity	0.00892***	0.00879***	0.00816***	-0.0391***	-0.0385***	-0.0334***
	(0.00252)	(0.00252)	(0.00233)	(0.00854)	(0.00853)	(0.00640)
VIX x Contract Intensity	0.0942			-0.593**		
	(0.0995)			(0.285)		
EPU x Contract Intensity		-0.116	-0.105		0.585	0.517
		(0.148)	(0.149)		(0.459)	(0.459)
WTI x CO2 intensity			0.00237			-0.0134
			(0.00274)			(0.00948)
Sample	Continuous	Continuous	Continuous	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	97863	97863	97863	440903	440903	440903
R-squared	0.689	0.689	0.689	0.786	0.786	0.787
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	3374	3374	3374	11033	11033	11033
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
First Year	1996	1996	1996	1990	1990	1990
Last Year	2018	2018	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Next, Table 6 examines the extent to which variations in climate policy uncertainty affect firm-level expenses in research and development and employment. As before, our specifications differentiate firms by their relative exposure to climate policy changes. Table 6 relies on quarterly series, as these variables are not available at the monthly level on Compustat.

One of the main challenges to achieve a successful transition towards a low-carbon economy is to create incentives to trigger firms' investment in low-carbon technologies. As anticipated, policy uncertainty introduces an element of risk for private companies which may affect their investment behavior. Sustained additional risk due to uncertainty about climate policy developments may therefore constitute a potential barrier to delivering the necessary low-carbon investments. At the same time, the direction of uncertainty is especially important in this context, as analyzed in section 4.4. In Table 6, we focus on the aggregate effect of a change in the CPU index.

Fist, we consider the impact of CPU on research and development. As with share prices, we find a moderately large and statistically significant negative coefficient on climate policy uncertainty changes for R&D expenses, particularly for firms with a high exposure to climate policy changes. These results are in line with predictions from the real options theory. High levels of uncertainty may depress firm-level investment by prompting preventive delays due to investment irreversibility (Dixit, 1989; Pindyck, 1988; Bloom et al., 2007), which is an especially important source of concern in the case of R&D investments (Dixit & Pindyck, 1994). Consider again the climate policy uncertainty changes from 2000 to 2018. Assuming a median exposure, the implied quarterly decreases in R&D expenses amount to almost 12%. In other words, in the absence of climate policy uncertainty, our estimates predict that research and development efforts since 2000 may have been greater by as much as one-tenth. Even in this case, the implied changes in R&D investments vary substantially across industries, ranging from an estimated modest decrease of around 2% for firms in Life Insurance (SIC 6311) to reductions of more than 16% for those operating in Fabricated Metal Products (SIC 3490). Finally, we explore the relationship between climate policy uncertainty and employment. These analyses rely on yearly data, as company-level employment data are available only at the annual level on Compustat. Our coefficients in Table 6 suggest that uncertainty about climate policy is associated with negative effects on annual employment levels, particularly for firms in high-emitting sectors. Working again with the changes in climate policy uncertainty from 2000 to 2018, we estimate that for a firm with median exposure the implied changes in annual employment is around 13%. The implied effects at the firm-level are relatively moderate if we consider that more than 80% of the companies in our estimation sample employ less than 10 workers (see Figure G.1 in Appendix G). Hence, the estimated relationship between CPU and aggregate employment levels is expected to be modest. Tables D.3 and D.4 in Appendix D further investigates the relationship of climate policy uncertainty changes to the cross-sectional structure of employment levels and R&D investment rates across different industries.

Table 6: **Effects of climate policy uncertainty on R&D expenses and employment in the US. 1990 - 2018 (quarterly series).**

	R&D			**Employment**		
	(1)	(2)	(3)	(1)	(2)	(3)
CPU x CO2 intensity	-0.0296**	-0.0295**	-0.0312***	-0.0627***	-0.0630***	-0.0364***
	(0.0128)	(0.0128)	(0.0109)	(0.00809)	(0.00810)	(0.00560)
VIX x Contract Intensity	-0.416			-0.382		
	(0.457)			(0.244)		
EPU x Contract Intensity		0.0430	0.0596		-0.330	-0.482*
		(0.831)	(0.828)		(0.288)	(0.288)
WTI x CO2 intensity			0.00577			-0.0384***
			(0.0147)			(0.00624)
Sample	Continuous	Continuous	Continuous	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	94915	94915	94915	79465	79465	79465
R-squared	0.889	0.889	0.889	0.943	0.943	0.943
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	3038	3038	3038	8273	8273	8273
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Year	Year	Year
First Year	1990	1990	1990	1990	1990	1990
Last Year	2018	2018	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * p<0.10, ** p<0.05, *** p<0.01.

4.2 Robustness tests

This section presents a a number of additional results for robustness purposes. Our main robustness tests, as presented in what follows, include (1) the use of an alternative version of our index (N-CPU) introduced in Section 2.3; (2) a different estimation window that ensures comparability across all our outcome variables; (3) a number of other industry-level policy exposure measures.

Table 7 assesses the sensitivity of our results to an alternative version of our CPU index computed with a search strategy restricted to climate policy keywords (see Appendix A). By doing so, we investigate whether the differences in topical scope between the original and the restricted version of the index alter our estimations to a considerable degree. The key rationale is to verify whether our estimated relationships might be driven by uncertainty about policy developments targeting other environmental concerns, such as local air pollution, rather than climate regulation. Results in Table 7 are all comparable in terms of size and significance to those presented in Tables 4 - 6, suggesting that our estimations are fundamentally driven by uncertainty related to policies addressing climate change.

Table 7: **Effects of N-CPU on implied volatility, share prices, R&D expenses and employment in the US. 1990 - 2018 (quarterly series)**.

	(1)	(2)	(3)	(4)
	Volatility (30)	**Share Price**	**R&D**	**Employment**
CPU x Industry CO2 intensity	0.00860***	-0.0352***	-0.0312***	-0.0367***
	(0.00237)	(0.00654)	(0.0112)	(0.00548)
EPU x Contract Intensity	-0.104	0.517	0.0613	-0.482*
	(0.149)	(0.459)	(0.828)	(0.288)
WTI x Industry CO2 intensity	0.00218	-0.0123	0.00645	-0.0374***
	(0.00273)	(0.00940)	(0.0146)	(0.00620)
Sample	Continuous	Continuous	Continuous	Continuous
Search Strategy	Restricted	Restricted	Restricted	Restricted
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	97863	441044	94915	79512
R-squared	0.689	0.786	0.889	0.943
Clustered S.E.	Yes	Yes	Yes	Yes
Number of firms	3374	11033	3038	8276
Firm effects	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Year
First Year	1996	1990	1990	1990
Last Year	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * p<0.10, ** p<0.05, *** p<0.01.

Next, Table 8 explores whether our results change when running our estimations starting from 1996. Our implied volatility measure retrieved from Options Metrics is only available from 1996. Therefore, in order to test to what extent differences in terms of significance and magnitude between our estimates could be potentially explained by distinct estimation windows, we additionally estimate our main specifications using a common time frame, i.e. 1996 to 2018. Even in this case, we yield comparable results to Tables 4 - 6.

Table 8: **Effects of climate policy uncertainty on implied volatility, share prices, R&D expenses and employment in the US. 1996-2018.**

	(1)	(2)	(3)	(4)
	Volatility (30)	**Share Price**	**R&D**	**Employment**
CPU x Industry CO2 intensity	0.00816***	-0.0354***	-0.0346***	-0.0371***
	(0.00233)	(0.00667)	(0.0113)	(0.00574)
EPU x Contract Intensity	-0.105	0.652	-0.407	-0.443
	(0.149)	(0.504)	(0.917)	(0.278)
WTI x Industry CO2 intensity	0.00237	-0.0125	0.00509	-0.0329***
	(0.00274)	(0.00918)	(0.0134)	(0.00596)
Sample	Continuous	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	97863	384403	82217	66711
R-squared	0.689	0.796	0.894	0.951
Clustered S.E.	Yes	Yes	Yes	Yes
Number of firms	3374	10442	2865	7646
Firm effects	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Year
First Year	1996	1996	1996	1996
Last Year	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * p<0.10, ** p<0.05, *** p<0.01.

Finally, we consider additional industry-level economic policy exposure measures that we interact with the EPU index to investigate whether different approaches to measuring exposure to government policy risks affect our results. First, we interact the EPU index with the measure of exposure to climate policy risk described in Section 3.1.2. Results are presented in Table 9. The aim is to provide a direct comparison between our CPU and the EPU index. Overall, the estimated relationships between climate policy uncertainty and economic outcomes are still comparable to our main specifications. The coefficient on EPU, however, bears limited direct economic interpretation. Additionally, the two interacted terms tend to be highly correlated. Nevertheless, we see these result as additional supporting evidence that our index can be can be a significant predictor of firm-level economic outcomes even after controlling for the impacts of economic policy uncertainty.

Table 9: **Effects of climate policy uncertainty on implied volatility, share prices, R&D expenses and employment in the US. Alternative exposure measure (1)**.

	(1)	(2)	(4)	(4)
	Volatility (30)	**Share Price**	**R&D**	**Employment**
CPU x Industry CO2 intensity	0.00671***	-0.0318***	-0.0323***	-0.0590***
	(0.00180)	(0.00694)	(0.0105)	(0.00720)
EPU x Industry CO2 intensity	-0.00494**	-0.0139	0.0111	0.0242***
	(0.00214)	(0.00992)	(0.0123)	(0.00724)
Sample	Continuous	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	123871	520061	95708	87534
R-squared	0.711	0.794	0.889	0.941
Clustered S.E.	Yes	Yes	Yes	Yes
Number of firms	4366	13341	3079	9155
Firm effects	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Year
First Year	1996	1990	1990	1990
Last Year	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * p<0.10, ** p<0.05, *** p<0.01.

Second, we compute Herfindahl-Hirschman (HHI) concentration indices using Compustat information on sales and industry definitions. Within every SIC 4-digit industry, we sum up the squared ratios of firm sales to the total industry sales in the year prior to our estimation period. Then, we assign the estimated pre-sample industry-level HHI to each firm and interact it with the EPU index. Companies may exhibit different responses to changes in economic policy uncertainty depending on the amount of competition among them. On the one hand, firms in sectors where market power is more concentrated may be less sensitive to changes in EPU because they have more monopolistic positions. On the other hand, companies operating in more concentrated industries tend to be larger and more actively traded in the stock market, making them more exposed to regulatory risk changes. Results are presented in Table 10. Overall, both alternative measures and specifications all yield highly significant results similar to the results displayed in Tables 4 to 6 under specification (2).

Table 10: **Effects of climate policy uncertainty on implied volatility, share prices, R&D expenses and employment in the US. Alternative exposure measure (2)**.

	(1)	(2)	(3)	(4)
	Volatility (30)	**Share Price**	**R&D**	**Employment**
CPU x Industry CO2 intensity	0.00595**	-0.0373***	-0.0331***	-0.0571***
	(0.00248)	(0.00787)	(0.0128)	(0.00768)
EPU x HHI	0.0173	-0.196***	0.0144	0.000169
	(0.0108)	(0.0305)	(0.0390)	(0.0192)
Sample	Continuous	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	108472	518800	95586	87434
R-squared	0.689	0.794	0.889	0.941
Clustered S.E.	Yes	Yes	Yes	Yes
Number of firms	3706	13258	3074	9149
Firm effects	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Year
First Year	1996	1990	1990	1990
Last Year	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

4.3 Historical analysis

As discussed in Section 2.3, a pivotal aspect to investigate in the context of climate policy developments is the direction of the uncertainty. Throughout the years, climate action has experienced many instances of acceleration and deceleration. Greater uncertainty may arise either from expectations of additional delays in climate action or anticipated greater stringency in future climate regulation. In the following section, we provide historical breakdowns for our main specifications to investigate whether the direction of our estimated relationships changes in accordance to the underlying drivers of climate policy uncertainty.

Table 11 reports our estimated coefficients when running specification (2) from Tables 4 to 6 across consecutive shorter time frames in our sample. In line with our expectations, the direction of the estimated effects seems to change depending on the estimation window. For instance, although we primarily observe a significant and negative effect on share prices throughout the entire estimation period, this effect appears to turn positive between 2010 and 2014. This coincides with the 2010 withdrawal of the US climate change bill under the Obama administration as well as the President's retreat on stricter ozone standards over the following year. Such developments may have signaled additional delays in climate action at a national level, plausibly leading investors to revise their expectations of regulatory risk downwards. Intuitively, we would expect stock markets to make gains when new developments point to a setback in climate action, unless investors are thinking in terms of long-term climate goals. Similarly, the estimated effect for implied volatility turns negative from 2015 onward in stark contrast to the trend that characterized the preceding decade. This occurred in conjunction with the election of President Trump which represented a clear shift from the policy priorities and goals of the preceding administration's climate agenda. In addition, our results suggest that the change in direction of environmental policy in the United States under the Trump administration has been accompanied by significant reductions in R&D efforts.

Table 11: **Historical Breakdowns (quarterly series).**

Dependent Variable	**1990 - 1994**	**1995 - 1999**	**2000 - 2004**	**2005 - 2009**	**2010 - 2014**	**2015 - 2018**
Implied Volatility						
CPU x CO2 Intensity		0.00231	-0.00458	0.0170***	0.0132**	-0.0146***
		(0.00395)	(0.00565)	(0.00657)	(0.00555)	(0.00376)
Share Price						
CPU x CO2 Intensity	-0.00851*	-0.00723**	0.000502	-0.0370**	0.0357***	-0.00457
	(0.00503)	(0.00332)	(0.0116)	(0.0159)	(0.0135)	(0.00674)
R&D Expenses						
CPU x CO2 Intensity	-0.0218	0.0103	0.0581***	-0.0271	-0.0402*	-0.0462***
	(0.0134)	(0.00888)	(0.0157)	(0.0325)	(0.0232)	(0.0131)
Employment (Annual)						
CPU x CO2 Intensity	-0.0566***	0.0146	0.0352**	-0.0361**	0.00714	-0.0217***
	(0.0122)	(0.00964)	(0.0138)	(0.0166)	(0.0110)	(0.00581)

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. All specifications include firm and quarterly effects-Additionally, we control for the effect of log(EPU) x 4-digit Contract Intensity. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

4.4 Belief revision

A key question that arises at this point of the analysis is how economic outcomes respond to the different underlying drivers of uncertainty about climate policy. To this end, we turn to the sub-indices introduced in Section 2.3, namely O-CPU and P-CPU (see Appendix A). Making use of the sub-indices allows to systematically disentangle the effects of climate policy uncertainty when belief revision goes towards more or less climate action. The estimated coefficients using both indices are presented in Table 12.

Overall, these results suggest that economic outcomes are more sensitive to uncertainty about climate policy when expectations point towards more stringent regulation. Comparing the results for the two sub-indices, the coefficients on O-CPU consistently exhibit larger coefficients, in absolute value. This holds particularly true in the case of share prices. Stock market reactions appear to be remarkably more sensitive to uncertainty related to potential policy developments increasing climate ambition. This implies that the relationship between share prices and CPU estimated by our main specifications is likely to be primarily driven by belief revision towards more regulatory stringency. This also appears to be the case for the effect on employment. In fact, when regressing annual employment levels on each sub-index respectively, we only yield a significant coefficient for O-CPU. The difference in the estimated effects is less marked for the effects on implied volatility and R&D expenses.

Table 12: **Effects of climate policy uncertainty on volatility, share price, R&D expenses and employment in the US. 1990 - 2018 (quarterly series). Comparing P-CPU and O-CPU.**

	P-CPU				**O-CPU**			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Volatility (30)	**Share Price**	**R&D**	**Employment**	**Volatility (30)**	**Share Price**	**R&D**	**Employment**
CPU x Industry CO2 intensity	0.00631***	-0.0174***	-0.00730*	-0.00554	0.00850***	-0.0439***	-0.0174*	-0.0422***
	(0.00137)	(0.00267)	(0.00424)	(0.00338)	(0.00216)	(0.00636)	(0.0104)	(0.00552)
EPU x Contract Intensity	-0.124	0.548	0.0950	-0.394	-0.108	0.550	0.121	-0.426
	(0.146)	(0.459)	(0.836)	(0.291)	(0.149)	(0.457)	(0.827)	(0.289)
WTI x Industry CO2 intensity	0.00244	-0.0161*	0.00243	-0.0441***	0.00214	-0.00979	0.00423	-0.0353***
	(0.00275)	(0.00972)	(0.0150)	(0.00650)	(0.00271)	(0.00934)	(0.0144)	(0.00612)
Sample	Continuous	Continuous	Continuous	Continuous	Continuous	Continuous	Continuous	Continuous
Search Strategy	Negative	Negative	Negative	Negative	Positive	Positive	Positive	Positive
Exposure Measure	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant	Time-invariant
N	97196	437888	94104	79509	97863	441044	94915	79512
R-squared	0.689	0.787	0.889	0.943	0.689	0.787	0.889	0.943
Clustered S.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of firms	3372	11032	3038	8276	3374	11033	3038	8276
Firm effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time effects	Quarter	Quarter	Quarter	Year	Quarter	Quarter	Quarter	Year
First Year	1996	1990	1990	1990	1996	1990	1990	1990
Last Year	2018	2018	2018	2018	2018	2018	2018	2018
Specification	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * p<0.10, ** p<0.05, *** p<0.01.

5 Conclusions

Since private sector investments in low-carbon technologies are fundamentally dependent upon expectations over future climate policy stringency, an important barrier for private sector investment in such technologies may be policy uncertainty. Analyzing firms' and investors' responses to climate policy shocks is also crucial to devise the best possible approach to transition to a low-carbon economy, which may include a wide array of environmental, fiscal, innovation, and macroprudential policies. However, firms and investors may not only react to realized climate policy shocks, but also to changes in the probability of these shocks happening, which is what we define as climate policy uncertainty. Since climate change became a policy issue in the early 1980s, domestic and international climate policy has attempted, through periods of progress and others of setbacks, to move the economy from a carbon-intensive to a low-carbon equilibrium.

To capture firms' and investors' responses to climate policy uncertainty, we develop a novel newspaper-based index capturing climate policy uncertainty in several major economies and then study its relationship with a set of key firm-level outcomes for the United States, covering publicly-listed firms from 1980 onward. We analyze outcomes such as share price volatility and share price, employment decisions, and investments in research and development. Our approach also accounts for the fact that uncertainty may sometimes reflect a slowdown in the transition to a cleaner economy, and sometimes to a breakthrough or acceleration. As a result, we developed two sub-indices, capturing both sources of uncertainty.

Overall, we find that an increase in climate policy uncertainty is linked with larger implied stock price volatility as well as lower share prices. Similarly, climate policy uncertainty is negatively associated with R&D investments and annual employment.

The variation in R&D confirms previous research considering actual policy changes as source of variation, suggesting that firms base their decisions on whether to innovate not only based on regulatory changes, but also on expectations thereof. The negative, but rather small changes in employment are also consistent with the existing literature, which points to relatively small changes in employment following climate policy tightening. In all our results, the source of the uncertainty matters, though. In periods in which climate policy was stalling, several outcomes reacted positively to higher uncertainty, as it might have pointed to further divisions among legislators. Consistently, our sub-indices indicate stronger reactions to climate policy uncertainty when the latter is driven more by policy tightening than inaction,

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hémous, D. (2012). The environment and directed technical change. *American Economic Review*, 102(1):131–166.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1):1–51.

Ambec, S., Cohen, M. A., Elgie, S., and Lanoie, P. (2013). The Porter hypothesis at 20: Can environmental regulation enhance innovation and competitiveness? *Review of Environmental Economics and Policy*, 7(1):2–22.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636.

Banque de France (2019). Greening the financial system: The new frontier. Technical report, Banque de France.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F., and Visentin, G. (2017). A climate stress-test of the financial system. *Nature Climate Change*, 7(4):283–288.

Bernanke, B. S. (1983). Irreversibility, uncertainty, and cyclical investment. *The Quarterly Journal of Economics*, 98(1):85–106.

Bovenberg, A. L. and Smulders, S. (1995). Environmental quality and pollution-augmenting technological change in a two-sector endogenous growth model. *Journal of Public Economics*, 57(3):369–391.

Calel, R. and Dechezleprêtre, A. (2016). Environmental policy and directed technological change: Evidence from the European carbon market. *Review of Economics and Statistics*, 98(1):173–191.

Carattini, S., Heutel, G., and Melkadze, G. (2021). Climate policy, financial frictions, and transition risk. Technical Report w28525, National Bureau of Economic Research.

Carattini, S. and Sen, S. (2019). Carbon taxes and stranded assets: Evidence from Washington state. Technical Report 7785, CESifo Group Munich.

Carney, M. (2015). Breaking the tragedy of the horizon–climate change and financial stability. *Speech given at Lloyd's of London*, 29:220–230.

Diluiso, F., Annicchiarico, B., Kalkuhl, M., and Minx, J. C. (2021). Climate actions and macro-financial stability: The role of central banks. *Journal of Environmental Economics and Management*, 110:102548.

Dorsey, J. (2019). Waiting for the courts: Effects of policy uncertainty on pollution and investment. *Environmental and Resource Economics*, 74(4):1453–1496.

ECB (2021). Financial stability review. Technical Report May 2021.

Engle, R. F., Giglio, S., Kelly, B., Lee, H., and Stroebel, J. (2020). Hedging climate change news. *The Review of Financial Studies*, 33(3):1184–1216.

Fabrizio, K. R. (2013). The effect of regulatory uncertainty on investment: Evidence from renewable energy generation. *The Journal of Law, Economics, and Organization*, 29(4):765–798.

Handley, K. and Limão, N. (2015). Trade and investment under policy uncertainty: Theory and firm evidence. *American Economic Journal: Economic Policy*, 7(4):189–222.

Hassan, T. A., Hollander, S., van Lent, L., and Tahoun, A. (2019). Firm-level political risk: Measurement and effects. *The Quarterly Journal of Economics*, 134(4):2135–2202. Publisher: Oxford Academic.

Hassett, K. A. and Metcalf, G. E. (1999). Investment with uncertain tax policy: Does random tax policy discourage investment. *The Economic Journal*, 109(457):372–393.

Krueger, P., Sautner, Z., and Starks, L. T. (2020). The importance of climate risks for institutional investors. *The Review of Financial Studies*, 33(3):1067–1111.

Martin, R., de Preux, L. B., and Wagner, U. J. (2014). The impact of a carbon tax on manufacturing: Evidence from microdata. *Journal of Public Economics*, 117:1–14.

McDonald, R. and Siegel, D. (1986). The value of waiting to invest. *The Quarterly Journal of Economics*, 101(4):707–728.

Popp, D. (2002). Induced innovation and energy prices. *American Economic Review*, 92(1):160–180.

Porter, M. E. and van der Linde, C. (1995). Toward a new conception of the environment-competitiveness relationship. *The Journal of Economic Perspectives*, 9(4):97–118.

Rozenberg, J., Vogt-Schilb, A., and Hallegatte, S. (2018). Instrument choice and stranded assets in the transition to clean capital. *Journal of Environmental Economics and Management*.

Rudebusch (2021). Climate change is a source of financial risk. *FRBSF Economic Letter*.

Sen, S. and von Schickfus, M.-T. (2020). Climate policy, stranded assets, and investors' expectations. *Journal of Environmental Economics and Management*, 100:102277.

Tobin, P., Schmidt, N. M., Tosun, J., and Burns, C. (2018). Mapping states' Paris climate pledges: Analysing targets and groups at COP 21. *Global Environmental Change*, 48:11–21.

van der Ploeg, F. and Rezai, A. (2020a). The risk of policy tipping and stranded carbon assets. *Journal of Environmental Economics and Management*, 100:102258.

van der Ploeg, F. and Rezai, A. (2020b). Stranded assets in the transition to a carbon-free economy. *Annual Review of Resource Economics*, 12(1).

Vermeulen, R., Schets, E., Lohuis, M., Kölbl, B., Jansen, D.-J., and Heeringa, W. (2018). An energy transition risk stress test for the financial system of the Netherland. Technical Report Volume 16 - 7, De Nederlandsche Bank.

World Bank (2020). State and Trends of Carbon Pricing – 2020. Technical report, Washington, DC.

Yamazaki, A. (2017). Jobs and climate policy: Evidence from British Columbia's revenue-neutral carbon tax. *Journal of Environmental Economics and Management*, 83:197–216.

Appendix

A Keyword selection

The following subsections report the keyword selection for our free-text search strategies in Factiva in all languages.

A.1 English

Original Search Strategy: (energy or "the environment" or environmental* or "climate change" or "global warming" or climate not ("business climate" or "political climate" or "economic climate" or "regulatory climate" or "legal climate") or carbon or emission* or "greenhouse gas" or GHG or "carbon dioxide" or CO2 or methane or CH4 or pollut* or "sulphur oxide" or "sulfur oxide" or SOx or "sulphur dioxide" or "sulfur dioxide" or SO2 or "nitrogen oxide" or NOx or "nitrogen dioxide" or NO2 or "particulate matter" or "fine particulates" or "fine particle" or "PM2.5" or "PM10" or ozone or renewable or hydro or "wind power" or "wind energy" or "wind farm" or "wind farms" or "wind turbine" or "wind turbines" or photovoltaic or PV or solar or biomass or "electric vehicle" or "electric vehicles" or "electric car" or "electric cars" or "hybrid vehicle" or "hybrid vehicles" or EV) same ((policy not “monetary policy”) or policies or regulation* or legislation* or law or laws or fee or fees or tax or taxes or standard or standards or certificate* or subsidy or subsidies or pricing or ETS or feed-in-tariff* or "trading scheme" or "trading system" or "cap and trade" or "emissions trading" or label or "eco-label") and (unclear or vague or uncertain or uncertainty)

Restricted Search Strategy (N-CPU): (energy or “the environment” or environmental* or "climate change" or "global warming" or (climate not ("business climate" or "political climate" or "economic climate" or "regulatory climate" or "legal climate")) or carbon or emission* or "greenhouse gas" or GHG or "carbon dioxide" or CO2 or methane or CH4 or renewable or hydro or "wind power" or "wind energy" or "wind farm" or "wind farms" or "wind turbine" or "wind turbines" or photovoltaic or PV or solar or biomass or "electric vehicle" or "electric vehicles" or "electric car" or "electric cars" or "hybrid vehicle" or "hybrid vehicles" or EV) same ((policy not "monetary policy") or policies or regulation* or legislation* or law or laws or fee or fees or tax or taxes or standard or standards or certificate* or subsidy or subsidies or pricing or ETS or feed-in-tariff* or "trading scheme" or "trading system" or "cap and trade" or "emissions trading" or label or "eco-label") and (unclear or vague or uncertain or uncertainty)

Search Strategy with additional keywords related to progress (O-CPU): (energy or "the environment" or environmental* or "climate change" or "global warming" or climate not ("business climate" or "political climate" or "economic climate" or "regulatory climate" or "legal climate") or carbon or emission* or "greenhouse gas" or GHG or "carbon dioxide" or CO2 or methane or CH4 or pollut* or "sulphur oxide" or "sulfur oxide" or SOx or "sulphur dioxide" or "sulfur dioxide" or SO2 or "nitrogen oxide" or NOx or "nitrogen dioxide" or NO2 or "particulate matter" or "fine particulates" or "fine particle" or "PM2.5" or "PM10" or ozone or renewable or hydro or "wind power" or "wind energy" or "wind farm" or "wind farms" or "wind turbine" or "wind turbines" or photovoltaic or PV or solar or biomass or "electric vehicle" or "electric vehicles" or "electric car" or "electric cars" or "hybrid vehicle" or "hybrid vehicles" or EV) same ((policy not "monetary policy") or policies or regulation* or legislation* or law or laws or fee or fees or tax or taxes or standard or standards or certificate* or subsidy or subsidies or pricing or ETS or feed-in-tariff* or "trading scheme" or "trading system" or "cap and trade" or "emissions trading" or label or "eco-label") and (unclear or vague or uncertain or uncertainty) **and (progress or implementation or adoption or consensus or action or success or achievement)**

Search Strategy with additional keywords related to failure (P-CPU): (energy or "the environment" or environmental* or "climate change" or "global warming" or climate not ("business climate" or "political climate" or "economic climate" or "regulatory climate" or "legal climate") or carbon or emission* or "greenhouse gas" or GHG or "carbon dioxide" or CO2 or methane or CH4 or pollut* or "sulphur oxide" or "sulfur oxide" or SOx or "sulphur dioxide" or "sulfur dioxide" or SO2 or "nitrogen oxide" or NOx or "nitrogen dioxide" or NO2 or "particulate matter" or "fine particulates" or "fine particle" or "PM2.5" or "PM10" or ozone or renewable or hydro or "wind power" or "wind energy" or "wind farm" or "wind farms" or "wind turbine" or "wind turbines" or photovoltaic or PV or solar or biomass or "electric vehicle" or "electric vehicles" or "electric car" or "electric cars" or "hybrid vehicle" or "hybrid vehicles" or EV) same ((policy not "monetary policy") or policies or regulation* or legislation* or law or laws or fee or fees or tax or taxes or standard or standards or certificate* or subsidy or subsidies or pricing or ETS or feed-in-tariff* or "trading scheme" or "trading system" or "cap and trade" or "emissions trading" or label or "eco-label") and (unclear or vague or uncertain or uncertainty) **and (slowdown or delay or disagreement or failure or rejection or postponement or setback)**

A.2 French

("l'énergie" or énergétiqu* or environmenta* or écologique* or "changement climatique" or "réchauffement climatique" or climatique* or pollution or polluant* or carbone or "gaz à effet de serre" or "dioxyde de carbone" or CO2 or méthane or CH4 or "oxyde de soufre" or SO2 or "dioxyde de soufre" or SOx or "oxyde d'azote" or NOx or "dioxyde d'azote" or "particules fines" or PM2,5 or PM10 or ozone or éolien* or (solaire* not "système solaire") or photovoltaïque* or hydraulique* or biomasse or "énergies renouvelables" or "énergie renouvelable" or "voitures électriques" or "voiture électrique" or "voiture hybride" or "voitures hybrides") same ((politiqu* not "politique monétaire") or réglementation* or lois or loi or redevance* or tax* or impôt* or norme* or tarification* or "tarif de rachat" or certificat* or subvention* or ETS or "marché d'émissions" or "droits à polluer" or "système d'échanges" or "SEQE") and (incertitude* or incertain or incertaine or incertains or incertaines or "peu clair" or "pas clair")

A.3 German

(Energiewende or "Erneuerbare*Energien*Gesetz" or "EEG-Einspeisevergütung" or "EEG-Umlage" or Klimapolitik or Energiepolitik or Umweltpolitik or Lufreinhaltepolitik or Luftreinhalteplan or ("die Umwelt" or ökologisch or Klimawandel or Erderwärmung or "globale Erwärmung" or "Klimaerwärmung" or "das Klima" or "dem Klima" or "des Klimas" or Klima?* or "die Umwelt" or "der Umwelt" or Umwelt?* or "die Energie" or "der Energie" or Energie?* not (Geschäftsklima or "politisches Klima" or "wirtschaftliches Klima" or "Wirtschaftsklima" or "Regulierungsklima" or "regulatorisches Klima" or "Rechtsklima" or "rechtliches Klima" or "gesellschaftliches Klima" or "Gesellschaftsklima") or Kohlenstoff* or Treibhausgas* or THG* or Kohlendioxid* or Kohlenstoffdioxid* or CO2* or Methan* or CH4* or Schadstoff* or Umweltverschmutzung* or Luftverschmutzung* verschmutz* or Schwefeloxid* or SOx* or Schwefeldioxid* or SO2* or Stickoxid* or NOx* or

Stickstoffdioxid* or NO2* or Partikel* or Feinpartikel* or Feinstaub* or PM2,5 or PM10* or Ozon* or erneuerbar* or Hydro* or Windenergie* or Windpark* or Windkraftanlage* or Photovoltaik* or PV or Solar* or Biomasse* or Elektrofahrzeug* or Elektroauto* or "E-Auto*" or Hybridfahrzeug* or Hybridauto*) same ((Politik nicht Geldpolitik) or Richtlinie or Richtlinien or Reform or Reformen or Regulierung or Regulierungen or Vorschrift or Vorschriften or Gesetz or Gesetze or Gebühr or Gebühren or Abgabe or Abgaben or Maßnahme or Maßnahmen or Steuer or Steuern or Standard or Standards or Zertifikat or Zertifikate or Subvention or Subventionen or Preisgestaltung or Emissionshandel or ETS or Einspeisetarif or Einspeisetarife or Einspeisevergütung or Einspeisevergütungen or Handelssystem or Handelssysteme or "Cap and Trade" or Emissionshandel or Label or Kennzeichen or "Umweltzeichen" or "Umweltabzeichen" or Umlage)) and (unklar or vage or unsicher or Unsicherheit)

A.4 Spanish

("la energía" or energétic* or "medio ambient*" or ecológic* or "cambio climático" or "calentamiento global" or climatic? or contaminación or contaminante* or polución or carbono or "gases de efecto invernadero" or "dióxido de carbono" or CO2 or metano or CH4 or "óxido de azufre" or SO2 or "dióxido de azufre" or SOx or "óxido de nitrógeno" or NOx or "dióxido de nitrógeno" or "partículas finas" or "partículas en suspensión" or PM2.5 or PM10 or ozono or eólic?* or "tecnología* solar*" or "panel* solar*" or "placa* solar*" or "central* solar*" or fotovoltaic* or "energía hidráulica" or hidroeléctric* or biomasa or "energías renovables" or "energías verdes" or "energías alternativas" or "energías limpias" or "renovables" or "auto* eléctrico*" or "coche* eléctrico*" or "auto* híbrido*" or "coche* híbrido*") same ((política* not "política monetaria") or regulación* or ley or leyes or impuesto* or estándar* or "tarifa de alimentación" or certificado* or subsidio* or ETS or "mercado* de emision*" or "derecho* a contaminar" or "sistema de comercio" or "ETS") and (incertidumbre* or inciert?* or "no es clar?" or “no está clar?" or "no son clar?s" or "no están clar?s")

A.5 Italian

(energia or energetic* or "l'ambiente" or ambiental* or ecologic* or “riscaldamento globale” or climatic* or carbonio or (emissioni not("emissioni obbligazionarie" or "emissioni del Tesoro")) or “gas a effetto serra” or “gas ad effetto serra” or “gas serra” or “anidride carbonica” or CO2 or metano or CH4 or inquinament* or inquinante or “ossid? di zolfo” or SOx or “diossido di zolfo” or “biossido di zolfo” or “anidride solforosa” or “SO2” or “ossido di azoto” or “monossido di azoto” or NOx or “diossido di azoto” or “biossido di azoto” or NO2 or “particelle fini” or “particolato atmosferico” or “particelle solide” or “particelle piccole” or “polveri sottili” or “particolato grossolano” or “particolato” or “materiale particolato” or “PM?10” or “PM?2,5” or ozono or rinnovabil* or idroelettric* or idraulic* or eolic* or (solare not(“sistema solare” or “anno solare” or “eritema solare” or “ustione solare” or “trattamento solare”)) or fotovoltaic* or biomass* or “auto elettric*” or “vehicol* elettric*” or “auto ibrid*”) same ((politica not(“politica monetaria”)) or regolament? or regolamentazione or legislazione or legge or tasse or canon? or standard not(“Standard & Poor's”) or certificat* or * certificazion* or sussidi or sussidio or sovvenzion? or ETS or “Sistema ES” or “feed?in?tariff*” or “conto energia” or “scambio di quote” or "regime di scambio" or "sistema di scambio " or "decarbonizzazione" or “effetto serra” or "cap and trade" or “mercato dei diritti per l'emissione” or “etichett* ambiental*” or norma or norme or “marchio ambientale” or eco-etichett* or “etichett* ecologic*” or “eco-label” or normative or normativa) and (incerto or incerti or incertezza or incertezze) not (spread or bond)

B Short climate policy history

B.1 United States

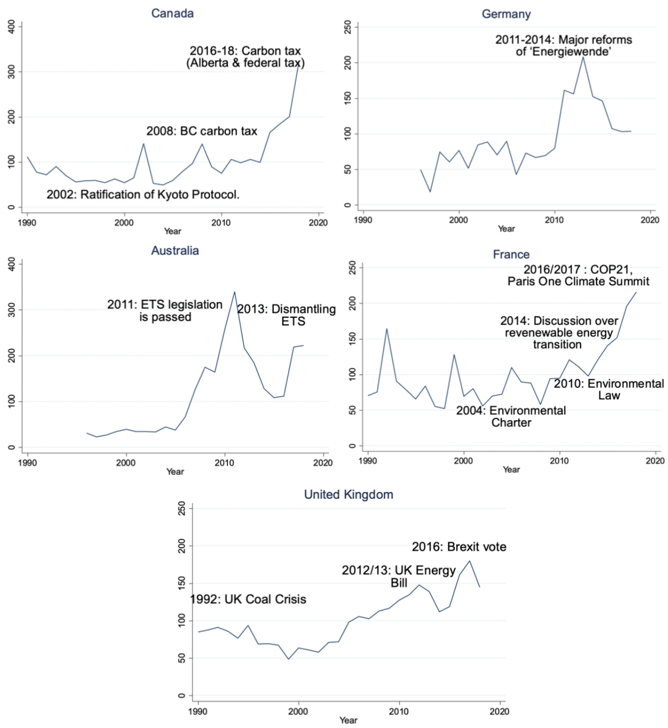
- **1970**. National Environmental Policy Act (NEPA) signed by President Nixon - "The Environmental Decade".
- **1980**. Carter signed into law a bill that established Superfund.
- **1980**. Congress appointed the National Academy of Sciences to carry out a comprehensive study on the impacts of rising CO_2 emissions.
- **1981**. For the first time, a federal agency (EPA) declared that global warming was "not a theoretical problem but a threat whose effects will be felt within a few years", with potentially "catastrophic" consequences.
- **1988**. The IPCC was established by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP).
- **1990**. Finland is the first country in the world to introduce a carbon tax (followed the year after by Sweden and Norway).
- **1990**. Amendments to the Clean Air Act of 1970: substantially increased the authority and responsibility of the federal government (i.e. introduction of a SO_2 cap-and-trade program).
- **1992**. Bush opposed international efforts at the Earth Summit in Rio de Janeiro, Brazil - "new rules to limit carbon dioxide emissions would hurt economic growth".
- **1997**. The US Senate voted unanimously under the Byrd-Hagel Resolution that the United States would not be ratifying the Kyoto Protocol.

- **2001**. President Bush released his National Energy Policy ("NEP")
- **2003**. The Clear Skies Act fails to become federal law of the United States.
- **2005**. The European Union Emissions Trading System (EU ETS) was launched.
- **2009**. President Barack Obama in his inaugural address called for the expanded use of renewable energy to meet the challenges of energy security and climate change.
- **2011**. Obama Administration abandons plans for stricter ozone standards proposed from the Environmental Protection Agency that would have significantly reduced emissions of smog-causing chemicals.
- **2015-2016**. The United States became a signatory to the Paris Agreement.
- **2017**. President-elected Donald Trump announced that the U.S. would cease all participation in the 2015 Paris Agreement.

C CPU index: extensions and other countries

C.1 CPU indices for Australia, Canada, France, and Germany

Figure C.1: CPU over 5 countries



Note: Based on yearly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva and Nexis.

D Estimated Outcome Changes

In order to investigate the relationship of climate policy policy uncertainty changes to the cross-sectional structure of stock market returns, R&D investment rates and employment levels we compute the implied changes in our outcome variables from 2000 to 2018, relying on the estimation presented in Section 4.

Table D.1: Estimated changes in Stock-Price Volatilities associated with Climate Policy Uncertainty changes from 2000 to 2018 for firms in selected industries

Outcome Measure And Industry	**(1)** Carbon Intensity (log)	**(2)** ΔCPU (log points)	**(3)** Coeff. on Log(CPU)* Intensity	**Estimated Change (1x2x3) in %**
Implied Volatility				
Mining				
Mining And Quarrying Of Nonmetallic Minerals	11.97	40.5	0.00816	4.0
Crude Petroleum Natural Gas	11.24	40.5	0.00816	3.7
Metal Mining	10.53	40.5	0.00816	3.5
Bituminous Coal Lignite Mining	10.07	40.5	0.00816	3.3
Manufacturing				
Miscellaneous Fabricated Metal Products	12.97	40.5	0.00816	4.3
Cement, Hydraulic	12.71	40.5	0.00816	4.2
Miscellaneous Products of Petroleum Coal	11.97	40.5	0.00816	4.0
Agricultural Chemicals	11.91	40.5	0.00816	3.9
Pulp Mills	10.1	40.5	0.00816	3.3
Broadwoven Fabric Mills, Cotton	8.54	40.5	0.00816	2.8
Beverages	6.42	40.5	0.00816	2.1
Canned, Fruits, Veg, Preserves, Jams Jellies	5.93	40.5	0.00816	2.0
Cookies Crackers	4.12	40.5	0.00816	1.4
Transport				
Electric Services	12.69	40.5	0.00816	4.2
Deep Sea Foreign Transportation of Freight	9.21	40.5	0.00816	3.0
Natural Gas Distribution	8.45	40.5	0.00816	2.8
Refuse Systems	8.4	40.5	0.00816	2.8
Finance, Insurance and Real Estate				
Oil Royalty Traders	12.92	40.5	0.00816	4.3
Real Estate Investment Trusts	9.07	40.5	0.00816	3.0
Miscellaneous Business Credit Institution	3.31	40.5	0.00816	1.1
Life Insurance	2.22	40.5	0.00816	0.7
Services				
Engineering Services	7.46	40.5	0.00816	2.5
Personal Services	4.31	40.5	0.00816	1.4

Table D.2: Estimated changes in Share Prices associated with Climate Policy Uncertainty changes from 2000 to 2018 for firms in selected industries

Outcome Measure And Industry	**(1)** Carbon Intensity (log)	**(2)** ΔCPU (log points)	**(3)** Coeff. on Log(CPU)* Intensity	**Estimated Change (1x2x3) in %**
Share Prices				
Mining				
Mining And Quarrying Of Nonmetallic Minerals	11.97	40.5	0.0334	16.2
Crude Petroleum Natural Gas	11.24	40.5	0.0334	15.2
Metal Mining	10.53	40.5	0.0334	14.2
Bituminous Coal Lignite Mining	10.07	40.5	0.0334	13.6
Manufacturing				
Miscellaneous Fabricated Metal Products	12.97	40.5	0.0334	17.5
Cement, Hydraulic	12.71	40.5	0.0334	17.2
Miscellaneous Products of Petroleum Coal	11.97	40.5	0.0334	16.2
Agricultural Chemicals	11.91	40.5	0.0334	16.1
Pulp Mills	10.1	40.5	0.0334	13.7
Broadwoven Fabric Mills, Cotton	8.54	40.5	0.0334	11.6
Beverages	6.42	40.5	0.0334	8.7
Canned, Fruits, Veg, Preserves, Jams Jellies	5.93	40.5	0.0334	8.0
Cookies Crackers	4.12	40.5	0.0334	5.6
Transport				
Electric Services	12.69	40.5	0.0334	17.2
Deep Sea Foreign Transportation of Freight	9.21	40.5	0.0334	12.5
Natural Gas Distribution	8.45	40.5	0.0334	11.4
Refuse Systems	8.4	40.5	0.0334	11.4
Finance, Insurance and Real Estate				
Oil Royalty Traders	12.92	40.5	0.0334	17.5
Real Estate Investment Trusts	9.07	40.5	0.0334	12.3
Miscellaneous Business Credit Institution	3.31	40.5	0.0334	4.5
Life Insurance	2.22	40.5	0.0334	3.0
Services				
Engineering Services	7.46	40.5	0.0334	10.1
Personal Services	4.31	40.5	0.0334	5.8

Table D.3: Estimated changes in R&D Expenses associated with Climate Policy Uncertainty changes from 2000 to 2018 for firms in selected industries

Outcome Measure And Industry	**(1)** Carbon Intensity (log)	**(2)** ΔCPU (log points)	**(3)** Coeff. on Log(CPU)* Intensity	**Estimated Change (1x2x3) in %**
R&D Expenses				
Mining				
Mining And Quarrying Of Nonmetallic Minerals	11.97	40.5	0.0312	15.1
Crude Petroleum Natural Gas	11.24	40.5	0.0312	14.2
Metal Mining	10.53	40.5	0.0312	13.3
Bituminous Coal Lignite Mining	10.07	40.5	0.0312	12.7
Manufacturing				
Miscellaneous Fabricated Metal Products	12.97	40.5	0.0312	16.4
Cement, Hydraulic	12.71	40.5	0.0312	16.1
Miscellaneous Products of Petroleum Coal	11.97	40.5	0.0312	15.1
Agricultural Chemicals	11.91	40.5	0.0312	15.0
Pulp Mills	10.1	40.5	0.0312	12.8
Broadwoven Fabric Mills, Cotton	8.54	40.5	0.0312	10.8
Beverages	6.42	40.5	0.0312	8.1
Canned, Fruits, Veg, Preserves, Jams Jellies	5.93	40.5	0.0312	7.5
Cookies Crackers	4.12	40.5	0.0312	5.2
Transport, Communications, Electric, Gas and Sanitary Service				
Electric Services	12.69	40.5	0.0312	16.0
Deep Sea Foreign Transportation of Freight	9.21	40.5	0.0312	11.6
Natural Gas Distribution	8.45	40.5	0.0312	10.7
Refuse Systems	8.4	40.5	0.0312	10.6
Finance, Insurance and Real Estate				
Oil Royalty Traders	12.92	40.5	0.0312	16.3
Real Estate Investment Trusts	9.07	40.5	0.0312	11.5
Miscellaneous Business Credit Institution	3.31	40.5	0.0312	4.2
Life Insurance	2.22	40.5	0.0312	2.8
Services				
Engineering Services	7.46	40.5	0.0312	9.4
Personal Services	4.31	40.5	0.0312	5.4

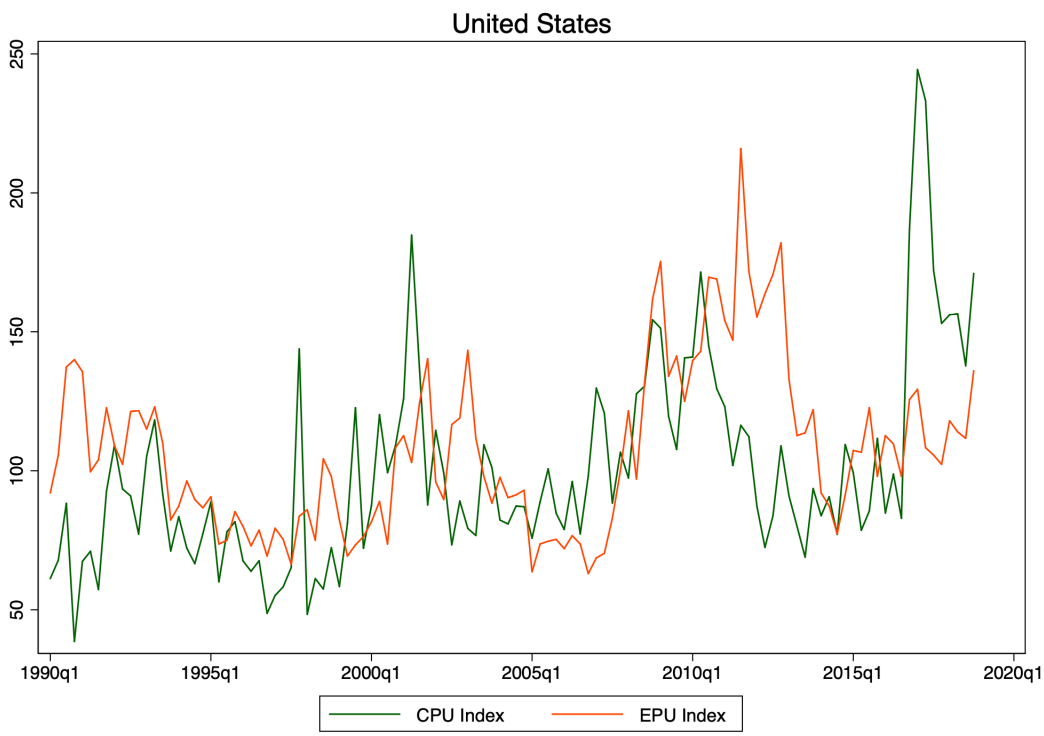
Table D.4: Estimated changes in Employment associated with Climate Policy Uncertainty changes from 2000 to 2018 for firms in selected industries

Outcome Measure And Industry	**(1)** Carbon Intensity (log)	**(2)** ΔCPU (log points)	**(3)** Coeff. on Log(CPU)* Intensity	**Estimated Change (1x2x3) in %**
Employment				
Mining				
Mining And Quarrying Of Nonmetallic Minerals	11.97	40.5	0.0364	17.6
Crude Petroleum Natural Gas	11.24	40.5	0.0364	16.6
Metal Mining	10.53	40.5	0.0364	15.5
Bituminous Coal Lignite Mining	10.07	40.5	0.0364	14.8
Manufacturing				
Miscellaneous Fabricated Metal Products	12.97	40.5	0.0364	19.1
Cement, Hydraulic	12.71	40.5	0.0364	18.7
Miscellaneous Products of Petroleum Coal	11.97	40.5	0.0364	17.6
Agricultural Chemicals	11.91	40.5	0.0364	17.6
Pulp Mills	10.1	40.5	0.0364	14.9
Broadwoven Fabric Mills, Cotton	8.54	40.5	0.0364	12.6
Beverages	6.42	40.5	0.0364	9.5
Canned, Fruits, Veg, Preserves, Jams Jellies	5.93	40.5	0.0364	8.7
Cookies Crackers	4.12	40.5	0.0364	6.1
Transport, Communications, Electric, Gas and Sanitary Service				
Electric Services	12.69	40.5	0.0364	18.7
Deep Sea Foreign Transportation of Freight	9.21	40.5	0.0364	13.6
Natural Gas Distribution	8.45	40.5	0.0364	12.5
Refuse Systems	8.4	40.5	0.0364	12.4
Finance, Insurance and Real Estate				
Oil Royalty Traders	12.92	40.5	0.0364	19.0
Real Estate Investment Trusts	9.07	40.5	0.0364	13.4
Miscellaneous Business Credit Institution	3.31	40.5	0.0364	4.9
Life Insurance	2.22	40.5	0.0364	3.3
Services				
Engineering Services	7.46	40.5	0.0364	11.0
Personal Services	4.31	40.5	0.0364	6.4

E Comparison of the CPU index to other relevant measures

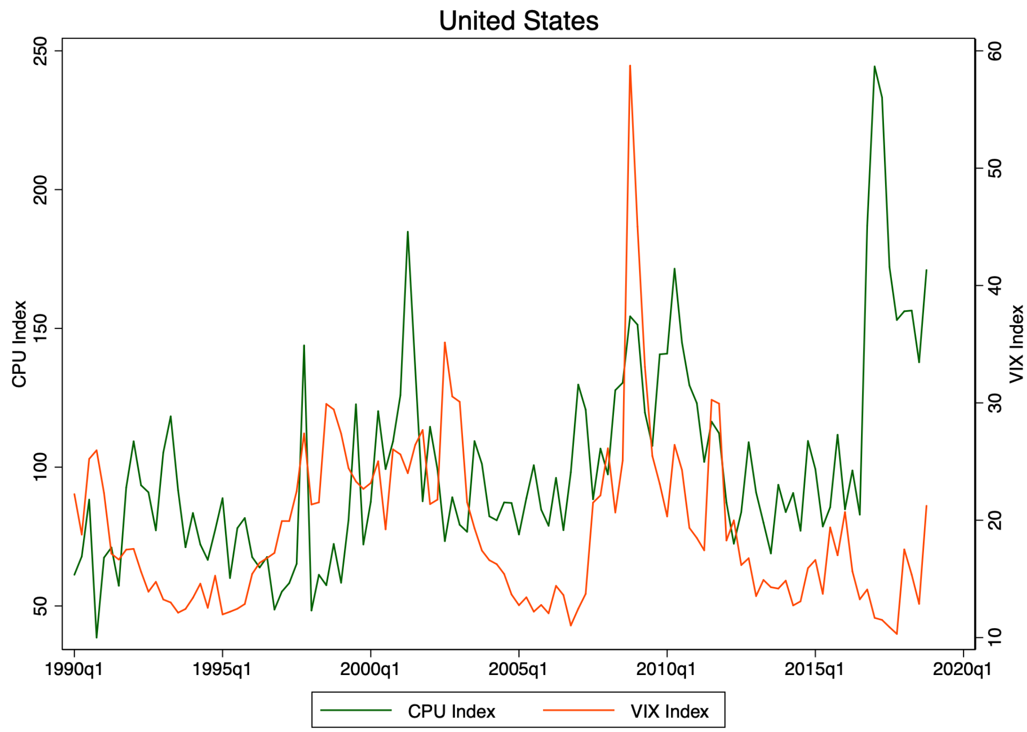
The followng section compares the evolution of the CPU index to other relevant uncertainty measures, such as the EPU from Baker et al. (2016), the Chicago Board Options Exchange's CBOE Volatility Index and oil price volatility as proxied by changes in West Texas Intermediate and Brent Crude.

Figure E.1: Comparing the evolution of the CPU to the EPU index developed by Baker et al. (2016)



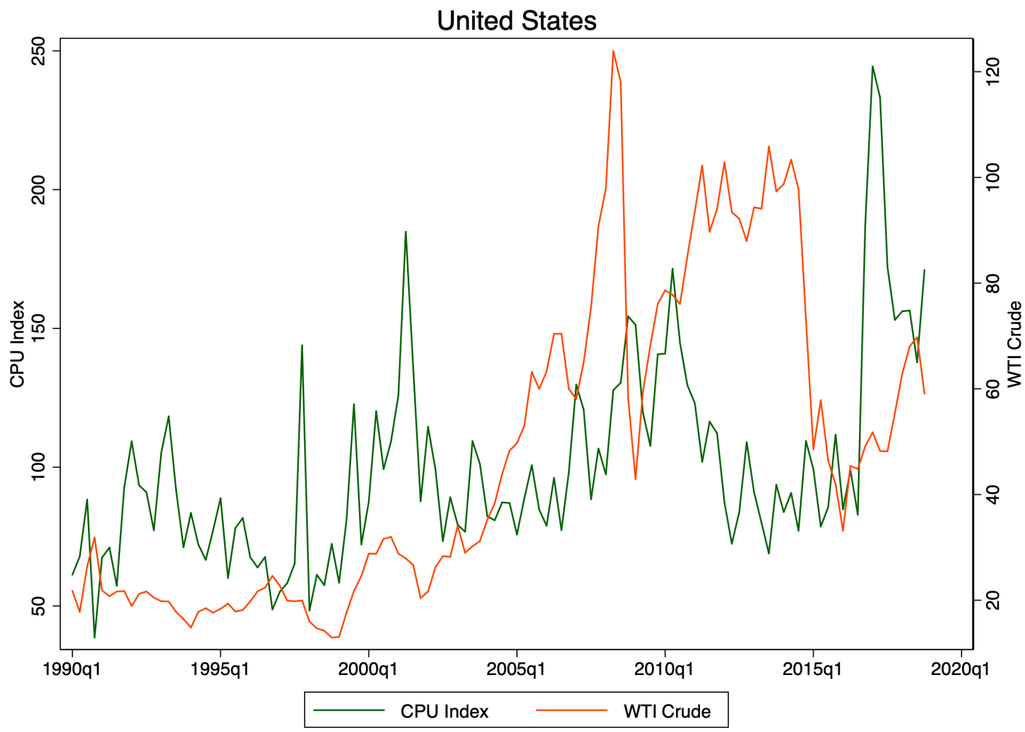
Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

Figure E.2: Comparing the evolution of the CPU to the VIX index



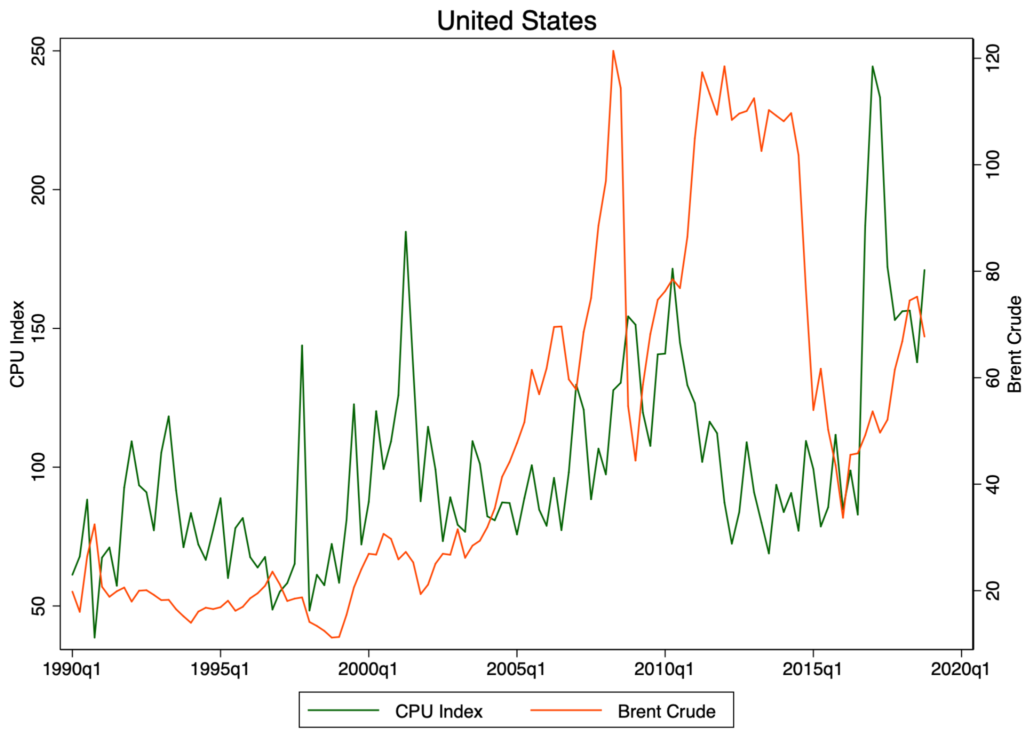
Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

Figure E.3: Comparing the evolution of the CPU to WTI Crude



Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

Figure E.4: Comparing the evolution of the CPU to Brent Crude



Note: Based on quarterly series from 1990 to 2018.
Source: Authors' own calculations based on newspaper articles from Factiva.

F Yearly time series

Table F.1: **Effects of climate policy uncertainty on implied volatility, share prices, R&D expenses and employment in the US (yearly series).**

	(1)	(2)	(3)
	Volatility (30)	**Share Price**	**R&D**
CPU x Industry CO2 intensity (out-of-sample)	0.0128***	-0.0485***	-0.0346***
	(0.00428)	(0.00944)	(0.0119)
EPU x Contract Intensity	-0.0975	0.881	1.128**
	(0.167)	(0.595)	(0.528)
WTI x Industry CO2 intensity (out-of-sample)	0.00702**	-0.0127	0.00590
	(0.00300)	(0.0101)	(0.0117)
Sample	Continuous	Continuous	Continuous
Search Strategy	Original	Original	Original
Exposure Measure	Time-invariant	Time-invariant	Time-invariant
N	28367	130194	43151
R-squared	0.730	0.779	0.898
Clustered S.E.	Yes	Yes	Yes
Number of firms	3358	11640	4587
Firm effects	Yes	Yes	Yes
Time effects	Year	Year	Year
First Year	1996	1990	1990
Last Year	2018	2018	2018
Specification	Exposure	Exposure	Exposure

Notes: Variables are averaged across months or quarters and expressed as natural logs. Standard errors in parentheses are based on clustering at the firm level. Sample is restricted to companies with consecutive observations over the whole period of time where they have been listed. CO_2 emissions are retrieved from the EPA Greenhouse Gas Reporting Program (GHGRP). Intensity measures are computed following the procedure described in Section 3.1.2. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

G Additional Descriptive Evidence

G.1 Employment levels in the estimation sample

Figure G.1: Frequency distribution of annual employment levels in the estimation sample