Organisation for Economic Co-operation and Development

ECO/WKP(2022)25

Unclassified **English - Or. English**

14 September 2022

ECONOMICS DEPARTMENT

MEASURING AND ASSESSING THE EFFECTS OF CLIMATE POLICY UNCERTAINTY

ECONOMICS DEPARTMENT WORKING PAPERS No. 1724

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JT03502329

Abstract/Résumé

MEASURING AND ASSESSING THE EFFECTS OF CLIMATE POLICY UNCERTAINTY

This study proposes a new indicator of Climate Policy Uncertainty based on newspaper coverage frequency. The indicator currently includes 12 OECD Member Countries and covers the period 1990-2018. The index spikes near major political events and during major discussions around potentially significant climate policy changes. Using a global firm-level dataset, the empirical analysis shows that Climate Policy Uncertainty is associated with economically and statistically significant decreases in investment, particularly in pollution-intensive sectors that are most exposed to climate policies, and among capital-intensive companies. In addition to annual series, the study also provides the indicator at higher frequencies of monthly and quarterly levels, and develops sub-indices that capture the direction of climate policy uncertainty associated with a strengthening or a weakening of climate policies for a sub-set of countries.

JEL classification: D22; D83; G10; O32; Q58
Keywords: Uncertainty, climate policy, investment, beliefs.

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MESURER ET ÉVALUER LES EFFETS DE L'INCERTITUDE DE LA POLITIQUE CLIMATIQUE

Cette étude propose un nouvel indicateur d'incertitude sur les politiques climatiques basé sur la couverture de ce thème dans la presse. L'indicateur couvre actuellement 12 pays membres de l'OCDE pour la période 1990-2018. Les pics dans l'indice ont lieu à proximité d'événements politiques majeurs et au moment de discussions importantes portant sur de potentiels changements majeurs dans la politique climatique. L'analyse empirique d'un ensemble de données mondiales d'entreprises montre que l'incertitude liée aux politiques climatiques est associée à des baisses économiquement et statistiquement significatives de l'investissement, en particulier dans les secteurs fortement polluants qui sont les plus exposés aux politiques climatiques, et parmi les entreprises à forte intensité capitalistique. En plus des séries annuelles, l'étude présente également l'indicateur à des fréquences plus élevées (aux niveaux mensuel et trimestriel), et développe des sous-indices qui capturent la direction de l'incertitude de la politique climatique associée à un renforcement ou un affaiblissement des politiques climatiques pour un sous-ensemble de pays.

Classification JEL: D22; D83; G10; O32; Q58
Mots clés : Incertitude, politique climatique, investissement, croyances.

Table of Contents

Tables

Figures

Measuring and evaluating the effect of Climate Policy Uncertainty

By Clara Berestycki, Stefano Carattini, Antoine Dechezleprêtre and Tobias Kruse[1]

1. Introduction

1. Over the next decades, vast amounts of investment in low-carbon infrastructure and technologies will be required to comply with the climate mitigation goals of the Paris Agreement and foster sustainable economic development. The OECD estimates that USD 6.9 trillion of annual investment in infrastructure will be needed until 2030 to meet climate and development objectives (OECD, 2017[1]). Global annual investments in low-carbon energy alone need to increase two-and-a-half times from USD 620 billion in 2018 to approximately USD 1.6 trillion by 2030 (IEA, 2019[2]). Any delays in those necessary investments are particularly problematic for climate change mitigation, since greenhouse gases (GHGs) such as CO_2 are stock pollutants, which accumulate over time in the atmosphere. Delayed investments in low-carbon technologies will therefore lead to higher levels of CO_2 concentrations, irreversibly amplifying climate change (Dorsey, 2019[3]) and might significantly increase the cost of transitioning to a low-carbon economy.

2. Currently, the private sector accounts for more than half of all green finance and climate investments (Climate Policy Initiative, 2018[4]), and private sector firms are expected to continue to play a key role in the development and diffusion of low-carbon technologies. It is therefore essential to understand and reduce the barriers that may prevent private firms to invest in climate-friendly technologies (Mazzucato, Semieniuk and Watson, 2015[5]).

3. Since private sector investments in climate-friendly technologies are fundamentally dependent upon expectations over future climate policy stringency, an important barrier for private sector investment in "green" technologies may be policy uncertainty. Policy uncertainty causes delays in firms' investment decisions, in particular for capital-intensive and irreversible investments (Bernanke, 1983[6]; McDonald and Siegel, 1986[7]; Pindyck, 1988[8]; Dixit and Pindyck, 1994[9]). Investments in energy infrastructure tend to be capital-intensive, are often irreversible and characterized by a long time-horizon, which requires a high level of certainty for planning purposes. Therefore, uncertainty in climate change mitigation policies, which make future market conditions less predictable, is frequently blamed for delaying firms' investments in low-carbon technologies and infrastructure. It is often argued that stable long-term policies are a necessary condition to achieve sufficient private investments into climate change mitigation technologies (Ambec et al., 2013[10]; Nemet et al., 2017[11]), but the impact that climate policy uncertainty may have on green

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investment and other outcomes is yet to be empirically analysed, by lack of an observable measure of policy uncertainty.

4. To investigate the role that policy uncertainty may play on investment, this study develops a new indicator of Climate Policy Uncertainty (CPU) based on newspaper[2] coverage frequency, following the methodology introduced by Baker, Bloom and Davis (2016[12]) to measure economic policy uncertainty. The index reflects the frequency of articles in leading newspapers that contain a trio of terms related to the environment (e.g. climate change, renewable energy, …); uncertainty (e.g. uncertain, unclear…); and policy (e.g. regulation, law, tax, standard…).

5. This new CPU indicator can be used by OECD governments to gauge the evolution of domestic climate policy uncertainty over time. It can also be used in empirical analyses to assess the impact of policy uncertainty on green investment, innovation, emissions reductions and other outcomes. Further, our indicator is complemented by two sub-indices, aimed at measuring whether the source of uncertainty is a possible acceleration in the process of decarbonisation (policy strengthening), or rather a possible deceleration (policy weakening).

6. At present, the CPU indicator focuses on 12 OECD countries: Australia, Canada, Chile, France, Germany, Ireland, Italy, Mexico, New Zealand, Spain, the United Kingdom and the United States. As the method to construct the indicator relies on keyword frequency counts in newspaper articles, the project focused on English-speaking countries to begin with and was subsequently expanded to include non-English speaking countries. The choice of non-English speaking countries is not random and influenced by the author' native languages as well as by efficiency considerations (e.g. Spanish allows to include three countries). Future versions of the indicator could include additional countries, bearing in mind that – as explained in Section 3 below – the search strategy has to be tailored to each specific language and country, which is particularly time-consuming. For a sub-set of countries the paper also reports the CPU indicator at higher frequencies of monthly and quarterly intervals.

7. The report is organised as follows. Section 2 presents some theoretical background on the role that policy uncertainty may play in the environmental sphere and reviews prior literature on the subject. Section 3 presents the methodology used to construct the indicator and shows the result of this on the set of 12 countries listed above. It also evaluates the validity of the indicator in several ways. Section 4 presents an application of firm-level econometric analysis of the impact of climate policy uncertainty on investment. Section 5 gives concluding remarks.

2. Background and previous literature

2.1. The impact of policy uncertainty

8. Starting in the 1980s, theoretical work on overall economic uncertainty suggested that high levels of uncertainty should give firms an incentive to delay investments and hiring when investment projects are costly to undo or workers are costly to hire and fire (Bernanke, 1983[6]; Pindyck, 1988[8]; Dixit and Pindyck, 1994[9]; Bretschger and Soretz, 2018[13]; Fried, Novan and Peterman, 2020[14]). This theoretical work was followed by

[2] The indicator is built using both print and online articles of newspapers.

empirical studies which established evidence for detrimental economic effects of monetary, fiscal, and regulatory policy uncertainty (Fernández-Villaverde et al., 2015[15]; Hassett and Metcalf, 2001[16]).

9. Empirical studies on the impact of policy uncertainty rely on the ability of researchers to construct high-quality indicators of this phenomenon, which is fundamentally unobserved and diffuse. A major step in this direction was achieved by Baker, Bloom and Davis (2016[12]), who developed a now widely-used indicator of overall economic policy uncertainty. They construct the index based on newspaper article counts. Using a search strategy to identify articles related to economic policy uncertainty, they construct a country-level index which varies at the monthly level. In the United States, the economic policy index spikes near tight presidential elections, the Gulf Wars, as well as the financial crisis. Merging the index with firm-level data, they show that economic policy uncertainty is associated with greater stock price volatility, as well as reduced investment and employment in policy-sensitive sectors like defence and healthcare.

10. Following the landmark paper by Baker, Bloom and Davis (2016[12]), other researchers have used their index and applied it in empirical settings to examine relationships with other economic outcome variables. Ashraf and Shen (2019[17]) show for instance that economic policy uncertainty is associated with higher interests on bank loans, as it may increase borrowers' default risk. Hsieh, Boarelli and Vu (2019[18]) show that it is significantly associated with US foreign direct investment (FDI), although with a time lag of between six months and three years. They find that higher levels of economic policy uncertainty in the United States are associated with increased outflows of capital to other countries. Similarly, higher levels of economic policy uncertainty in other countries are associated with a decline in inflow of US FDI into such countries. Handley and Limao (2017[19]) analyse the impact of trade policy uncertainty on consumer prices and income in the United States by analysing China's export boom to the United States following the WTO accession in 2001, showing that China's accession to the WTO lowered uncertainty which in turn lowered US prices and increased consumers' income significantly.

11. Empirical studies come to similar conclusions regarding the impact of regulatory uncertainty on innovation, as measured by patent filings. Cong and Howell (2018[20]) show that uncertainty concerning government intervention in initial public offerings in China has long-lasting negative effects on innovation. Bhattacharya (2017[21]) exploit close-elections to show that policy uncertainty negatively impacts innovation, particularly in innovation-intensive industries.

2.2. Climate Policy Uncertainty

12. In the context of climate policies, the importance of policy certainty for effective climate policy regulation and for stimulating investment in green technologies has been highlighted for many years. For example, the OECD has long emphasized the important role of policy certainty when considering investments with long time horizons, such as low-carbon investments (OECD/IEA, 2007[22]; OECD et al., 2015[23]; OECD, 2015[24]). Indeed, policy certainty increases the likelihood for firms to obtain financial returns from investments in environmental technologies (Porter and van der Linde, 1995[25]). Policy certainty is therefore posited to be a key driver in stimulating investments in such technologies.

13. Indeed, theoretical contributions that incorporate climate policy uncertainty into a general equilibrium framework come to the conclusion that climate policy uncertainty stalls

investments. Most of these approaches model uncertainty as a stochastic shock, either to taxes or to carbon prices. For example, Bretschger and Soretz (2018[13]) model uncertainty as a stochastic capital tax and show that this leads to suboptimal investment in green services, in turn creating a high risk-premium for green investments.

14. Empirical evidence on the impact of climate policy certainty on investment so far mostly comes from case studies on the renewable energy sector. Policy reviews and descriptive analyses have suggested that certainty seems to be a key determinant for the effectiveness and efficiency of support schemes in this sector (OECD/IEA, 2007[22]; De Jager et al., 2011[26]; Haas et al., 2011[27]). In-depth case studies of the evolution of renewable policies in Germany, Denmark, Spain, Greece, Canada and Switzerland highlight the importance of policy certainty for investment in solar PV (Farrell, 2009[28]; Mitchell, Bauknecht and Connor, 2006[29]; Lüthi, 2010[30]; Petrovich, Carattini and Wüstenhagen, 2021[31]), as do investor surveys (Lüthi and Wüstenhagen, 2012[32]; Bürer and Wüstenhagen, 2009[33]).

15. Mitchell, Bauknecht and Connor (2006[29]) argue for instance that the German feed-in tariff (FIT) has been able to credibly reduce investor risk by guaranteeing fixed rates for 20 years and more importantly, by not producing major changes in the FIT framework. This has led to substantial renewable energy and photovoltaic deployment since the enactment of the FIT in 1990 (Butler and Neuhoff, 2008[34]; IRENA, 2015[35]). By contrast, the Danish FIT, which was also enacted in the early 1990s and ensured rates for 20 years, was abruptly abandoned in 2003, causing widespread uncertainty and reducing PV deployment (Farrell, 2009[28]).

16. Econometric analyses of the role of renewable energy policy certainty across countries are rare because of difficulties in quantification and comparability (Lüthi and Prässler, 2011[36]). There are a few exceptions, however. For instance, Lüthi (2010[30]), in a cross-case study analysis of Germany, Spain and Greece, finds policy instability to be a critical determinant of investments in solar energy. Zhang (2013[37]) obtains similar results by explicitly incorporating the contract duration and digression rate in addition to the FIT rate into her analysis of the impact of FIT policies on wind energy deployment in Europe from 1991-2010. The author finds that longer contract duration is associated with increased deployment, while higher FIT rates are not. Using real options modelling, Reuter at al. (2012[38]) and Boomsma, Meade and Fleten (2012[39]) show that the uncertainty surrounding the renewal of FITs for renewable energy delays investment in Norway and Germany, while Zhu and Fan (2011[40]) come to a similar conclusion concerning investment in carbon capture and storage in China. Applying a similar method to the energy market more generally (where the uncertainty comes from variability in different scenarios of future CO_2 price paths), Fuss et al. (2009[41]) find a negative response of investment to regulatory uncertainty.

17. In contrast to case studies and modelling exercises, econometric analyses exploiting quasi-natural experiments to identify the effect of policy uncertainty are much more seldom. Fabrizio (2012[42]) measures regulatory stability by a state's history of passing and repealing energy legislation and finds that investments in renewable energy assets are lower for firms located in a state with a higher regulatory instability. Dorsey (2019[3]) studies the United States Clean Air Interstate Rule (CAIR) and uses legal challenges that create variation across states in the likelihood that firms would have to comply with the regulation. He finds that plants located in states subject to more uncertainty invest less in capital-intensive pollution-control technologies and reduce sulphur dioxide emissions by 13% less on average. A common limitation of these analyses is that they focus on a particular country

(the United States) and on specific policies, making it difficult to generalise the results beyond those. The objective of this project is to develop an indicator of climate policy uncertainty which can hold general lessons and allow for cross-country empirical studies.

18. It is important to note that, if most papers underline that climate policy uncertainty stalls overall investment (a scale effect), the impact on the *type* of investment is not as clear-cut, because uncertainty does not only increases the *variance* of anticipated policy stringency. It also modifies expectations about the predicted stringency *level* of future regulations. For example, Fried, Novan and Peterman (2020[14]) find that the risk of stricter climate policy in the future depresses overall investment but distorts investment towards a cleaner mix of capital because climate policy risk raises the expected return to clean capital relative to fossil. Combined with the decrease in the capital stock of all (including brown) firms, this leads to emissions reductions today. Similarly, Pommeret and Schubert (2018[43]) find that uncertainty over future decreases in the cap in an emissions permit system can in fact spur additional investments in emissions reductions technologies. In the renewable energy sector, uncertainty over whether production tax credits would be renewed (an downward revision of the future level of policy support) led to an investment spike in renewable capacity in the US, as project developers rushed to submit projects for approval of the subsidy (Barradale, 2010[44]).

3. Measuring Climate Policy Uncertainty

3.1. Methodology

19. This study builds upon the work of Baker, Bloom and Davis (2016[12]) in order to develop an indicator of climate policy uncertainty using the same approach. The methodology is presented in this section, and further details are available in Annex A.

20. To build their index of Economic Policy Uncertainty in the U.S., Baker, Bloom and Davis (2016[12]) 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”.

21. To build the index on Climate Policy Uncertainty (CPU), we similarly created a lexicon of words for each of the three components (Climate, Policy, and Uncertainty). The first category includes terms such as “CO_2”, or “climate change” which refer to a specific environmental or climate change concern. It also includes terms referring to technologies addressing these concerns such as “solar PV” or “renewable energy”. The second category includes terms related to policy making such as “regulation”, “legislation”, or “tax”, but also terms more specific to climate change mitigation policies such as “emissions trading system” or “cap and trade”. The third category includes the words “uncertain”, “uncertainty”, “vague” and “unclear”. Selected articles have to include at least one term from each category. The full list of keywords used in these three components are listed in Annex A.

22. To ensure that the selected articles focus on climate policy, and not the climate in one part and on unrelated policies in another, we imposed the restriction that terms from the policy category have to be located in the same paragraph as the respective keyword in the climate category. We thereby ensure that the two terms are related to each other in the newspaper article.

23. A 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 (e.g. climate change, renewable energy, clean transportation…). Baker, Bloom and Davis (2016[12]) 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 change-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.

24. Environmental policies cover an extensive range of issues related to pollution of air, water and soil; greenhouse gas emissions and climate change; biodiversity; waste management, etc. This version of the indicator mirrors the OECD's Environmental Policy Stringency indicator (Botta and Koźluk, 2014[45]) and focuses on policies related to climate change and air pollution. The focus on these issues has two advantages: first, it limits the number of keywords to be included, each of which can potentially generate false positives and therefore has to be checked individually (see below); secondly, it allows controlling for Environmental Policy Stringency in the econometric analyses conducted in Section 5, which is important as uncertainty is likely to increase when new policies are being discussed and implemented. However, the indicator can be easily extended to other areas by adding keywords to the search strategy depending on researchers' interests. Indeed, a major advantage of our methodology – compared to e.g. methods based on machine learning techniques – is that it is transparent, replicable and adaptable to specific needs. Further, the paper refers to the index as Climate Policy Uncertainty (CPU), because it captures mostly regulatory uncertainty related to climate policy. Indeed, a restricted version of the index that does not include any keywords related to local air pollution, which we call N-CPU (see Figure B.2. in Appendix B), correlates at 0.997 with our CPU index.

25. Two types of error may arise when building an indicator based on counts of newspaper articles: relevant articles may be left out (false negatives) and irrelevant articles may be included (false positives). The first potential error—exclusion of relevant articles—is the least problematic of the two. We can reasonably assume that we are able to capture only a certain proportion of all relevant articles. However, if this proportion is somewhat fixed across time, then the trend will still be valid. We cannot verify that false negatives are evenly distributed, however for our results to be biased the ratio of relevant articles we pick up would need to vary with macroeconomic conditions, which is unlikely. Hence, at the worst, our indicator can be seen as being a good proxy of the total number of articles about climate policy uncertainty. Because the proportion of excluded relevant articles might differ across languages and countries, we caution against cross-country comparisons regarding the *level* of policy uncertainty and focus instead on *within-country* variation.

26. The second error occurs if a selected set of keywords recovers articles that are not related to climate policy uncertainty. This possible inclusion of "false positives" is the main challenge in creating an indicator based on counts of newspapers articles. For example, a problem associated with 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". To reduce as much as possible the likelihood of including such false positives, we carefully read several hundreds of randomly selected articles and recursively adjusted the search strategy, excluding equivocal words and expressions (see details in Annex A).

27. Reading large samples of randomly selected articles enabled us to adjust the search strategy systematically to increase the ratio of relevant articles to around 90%, which is a reasonable compromise between including as many relevant articles as possible and minimizing the proportion of false positives. As there exists an inherent trade-off between recall (increasing the number of relevant articles) and precision (minimizing the number of false positives), we observed that going beyond the 90% threshold would imply excluding too many relevant articles.

28. If the remaining false positives are not randomly distributed over time, they could lead to spurious spikes in uncertainty. We therefore checked the distribution of false positives across time in the final search strategy based on a subset of randomly selected articles to ensure that the occurrence of false positives is equally low across time and not driving peaks in the index.

29. We initially created the lexicon in English in order to capture articles in English-speaking countries. The keywords were then translated in other languages by the authors and native speakers. When building the search strategies, we avoid as much as possible using country-specific terms. For example, we did not include the exact name of climate change or environment ministries, departments, or environmental protection agencies. The names of ministries or departments dealing with 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. However, a small number of country-specific keywords were added when absolutely necessary. An example is the German renewable energy legislation package “EEG” or “Erneuerbare Energien Gesetz”, which was included in the German search as it features so prominently in climate change-related discussions in Germany and returns a large number of relevant articles.

30. Importantly, we excluded articles that only talk about climate policy uncertainty within a different country (for example, an article in a French newspaper about uncertainty surrounding the German EEG). This ensures that the index is driven primarily by uncertainty within the country of analysis. The index may however include articles that discuss climate policy uncertainty both in the domestic and in a foreign country. Some events, such as the United States’ withdrawal from the Paris Agreement, can thus affect the index in other countries as well, but it is likely that this particular event also increased climate policy uncertainty in other countries beyond the United States since domestic climate change policy ambition is notoriously dependent on other countries’ commitments (Barrett and Stavins, 2003[46]).

31. The CPU Index covers the years from 1990 until 2018. Prior to 1990, the limited number of available newspaper sources make article counts less reliable. For Germany, Italy and Spain, the data is only available from the mid-1990s onwards. Chile and Mexico are only available from 2002.[3] We also construct higher frequency series, at the monthly and quartly level for a subset of countries. Constructing higher-frequency series is constrained by the availability of sufficiently granular newspaper articles because as the number of CPU articles per month or quarter becomes too small, the volatility in the index

[3] For Mexico the article counts identified by our search strategy are lower than for the other countries, making the series relatively volatile.

increases making it potentially driven by outliers. We are able to construct the monthly and quarterly series for the United States the United Kingdom, France and Germany.

32. To construct the indicator, we focus on major newspapers for each country to avoid including newspapers that only exceptionally report on the topic – a problem which is particularly relevant for climate policies – creating large volatility over time. The number of newspapers varies across countries, depending on the characteristics of national newspaper markets, as well as on data availability. To select newspapers, we started with information on newspaper circulation and asked colleagues from the respective countries to identify the main newspapers. We excluded all tabloid newspapers, even though they may have high circulation, to ensure the quality of the underlying articles. In a next step we verified the distribution of articles for these newspapers in Factiva and Nexis. Newspapers with incomplete coverage (such as Handelsblatt in Germany) or implausibly low numbers of articles had to be excluded. The newspapers include both print and online articles. Table 1 contains the full list of newspapers by country.

33. 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. Two online newspaper databases were used to download the article counts, Factiva and Nexis, which cover different sets of newspapers.[4]

34. As an illustration, Panel A in Figure 1 shows the annual article counts for the Wall Street Journal (US). The time series show the trends in articles on climate policy uncertainty (left axis) and in overall articles (right axis). The number of annual articles related to climate policy uncertainty varies between less than 50 and 450, with significant year-on-year variation. Overall, the frequency of articles on climate policy uncertainty appears to have increased since 2010, but the total number of articles published has increased as well.

Table 1. Newspaper coverage by country

Country	Newspapers covered in CPU Index
Australia	The Advertiser, The Age, The Australian, The Australian Financial Review, the Courier Mail, the Herald Sun, the Sydney Morning Herald
Canada	The Globe and Mail, Toronto Star, National Post, The Calgary Herald, Ottawa Citizen, Montreal Gazette
Chile	El Diario Financierio, El Mercurio
France	La Tribune, Le Figaro, Le Figaro Economie, Le Monde, Les Echos

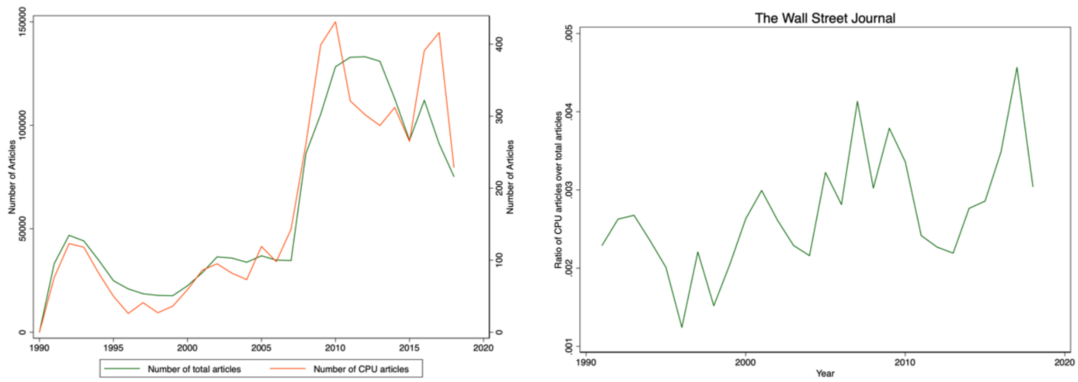
[4] The online newspaper databases Factiva and Nexis do not allow for web scraping of articles. Each database allows for online reading of articles, but bulk downloads of articles are not allowed, which would be required for a web scraping approach. We therefore downloaded the article counts that are picked up by our search strategy and read articles online within the database.

Germany	Die Süddeutsche Zeitung, die Welt
Ireland	The Irish Times, The Irish Independent
Italy	Il sole 24 ORE, la Repubblica, La Stampa, Il Corriere della Sera
Mexico	El Economista, El Financiero, El Universal
New Zealand	The New Zealand Herald, The Press
Spain	El Pais, El Mundo, Expansion
United Kingdom	The Financial Times, The Times, The Independent, The Telegraph, The Guardian
United States	The New York Times, The Washington Post, The Wall Street Journal

35. In order to account for this rising trend in total articles published – in particular driven by the digital revolution that transformed the newspaper industry, with online content that is typically broader than the print version – we first compute a simple newspaper-specific ratio of articles on climate policy uncertainty over the total article count by newspaper. Panel B in Figure 1 shows this ratio for the Wall Street Journal, obtained by dividing the CPU article count by the total article count. Dividing by the total number of articles is important to ensure that the index is not driven by newspaper-specific trends such as the overall increase of online articles. In the Wall Street Journal example, over time, between 1 and 5 in 1000 articles deal with climate policy uncertainty, 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. This ratio follows an upward trend but also varies significantly across years, with clear peaks in the early 1990s, early 2000s, around 2007-2009 and in 2017.

Figure 1. Article Counts in the Wall Street Journal (US)

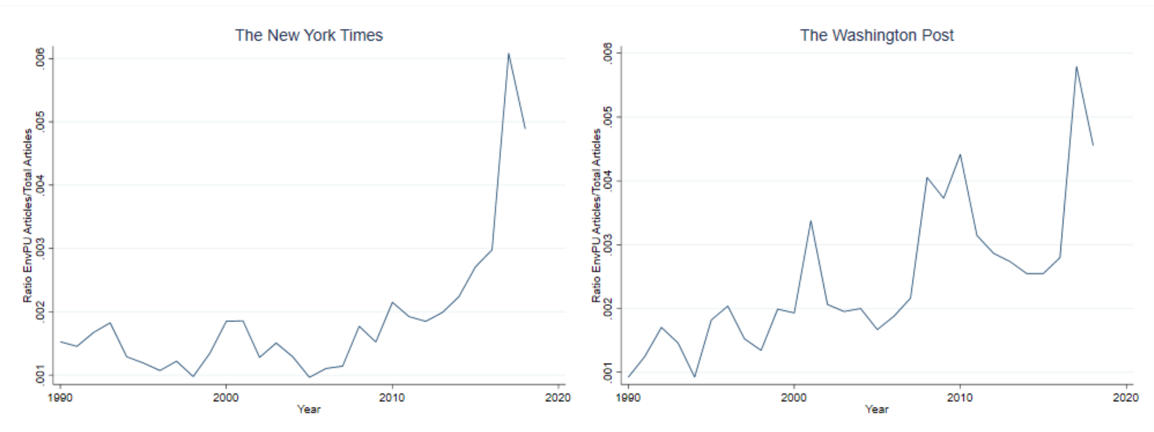
Panel A (raw counts) Panel B (ratio)



Note: Panel A shows the CPU Article counts in orange together with the total article counts in green for the United States Wall Street Journal. Panel B shows the ratio of CPU articles divided by total articles for the Wall Street Journal.
Source: Authors' calculations from Factiva

36. For each country, we compute the ratio of climate policy uncertainty articles over total article count for each newspaper considered. For the United States, these include the New York Times and the Washington Post in addition to the Wall Street Journal (Figure 2). The Washington Post follows a similar trend as the Wall Street Journal, but the New York Times appears different, with a much larger peak in 2017, even though the earlier spikes around 2000 and 2010 are also visible. This variation across newspapers illustrates the advantage of averaging data across several journals within each country in order to reduce volatility coming from a particular newspaper.

Figure 2. Ratio of Climate Policy Uncertainty Articles over Total Articles for the New York Times and the Washington Post (US)



Source: Authors' own calculations from Factiva.

37. 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, Bloom and Davis (2016[12]) 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 1 and Figure 2. 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.

38. The indicator provides information on *within-country* variation in climate policy uncertainty over time. On the other hand, descriptive cross-country comparison in the level of the index should be avoided, because of the standardization method, the different nature of news coverage across countries and the use of country-specific terms in our search strategy. In empirical analyses, such cross-country differences can be easily controlled for by the inclusion of country fixed effects, making it possible to carry out cross-country analysis.

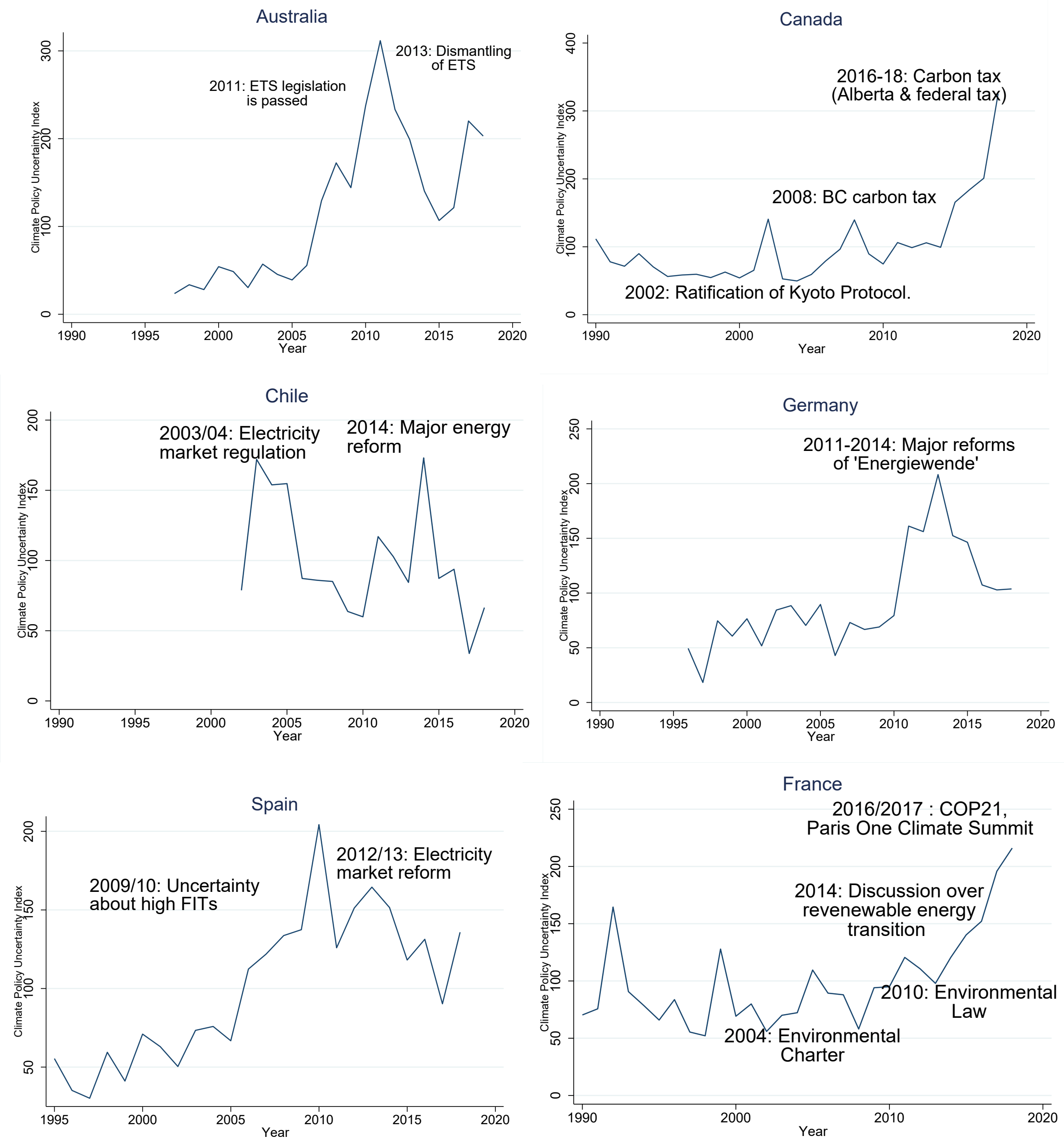
3.2. Main indicator

39. Figure 3 and Figure 4 show the resulting index over the time period 1990 to 2018 for the 12 countries in our sample. A number of messages come out of these figures. First, within each country, there is significant year-on-year variation, with notable peaks at different points in time followed by periods of lower uncertainty. This suggests that the indicator is able to pick up country-specific events. Second, even if climate policy uncertainty tends to have increased in the recent period in most countries, the trends differ significantly across countries, with important decreases in Australia, Germany, Italy and Spain in recent years compared to other countries such as Canada, France, the United Kingdom and the United States, which feature significant increases recently. This ability of the indicator to track country-specific temporal variation is critical to enable empirical analyses.

40. To further validate our index, and following Baker, Bloom and Davis (2016[12]), we link the country-specific peaks to relevant events – such as the discussion or implementation of major climate policies – by reading the headlines of the first hundred articles downloaded for the peak years in each country. Figures 3 and 4**Error! Reference source not found.** show the events associated with these spikes. In all countries, the peaks nearly all correspond to discussions on and reforms to either weaken existing climate regulations, or to implement new and strengthen existing climate policies. Few peaks in our index are driven by more general uncertainty spikes that have direct implications on climate or energy policies.

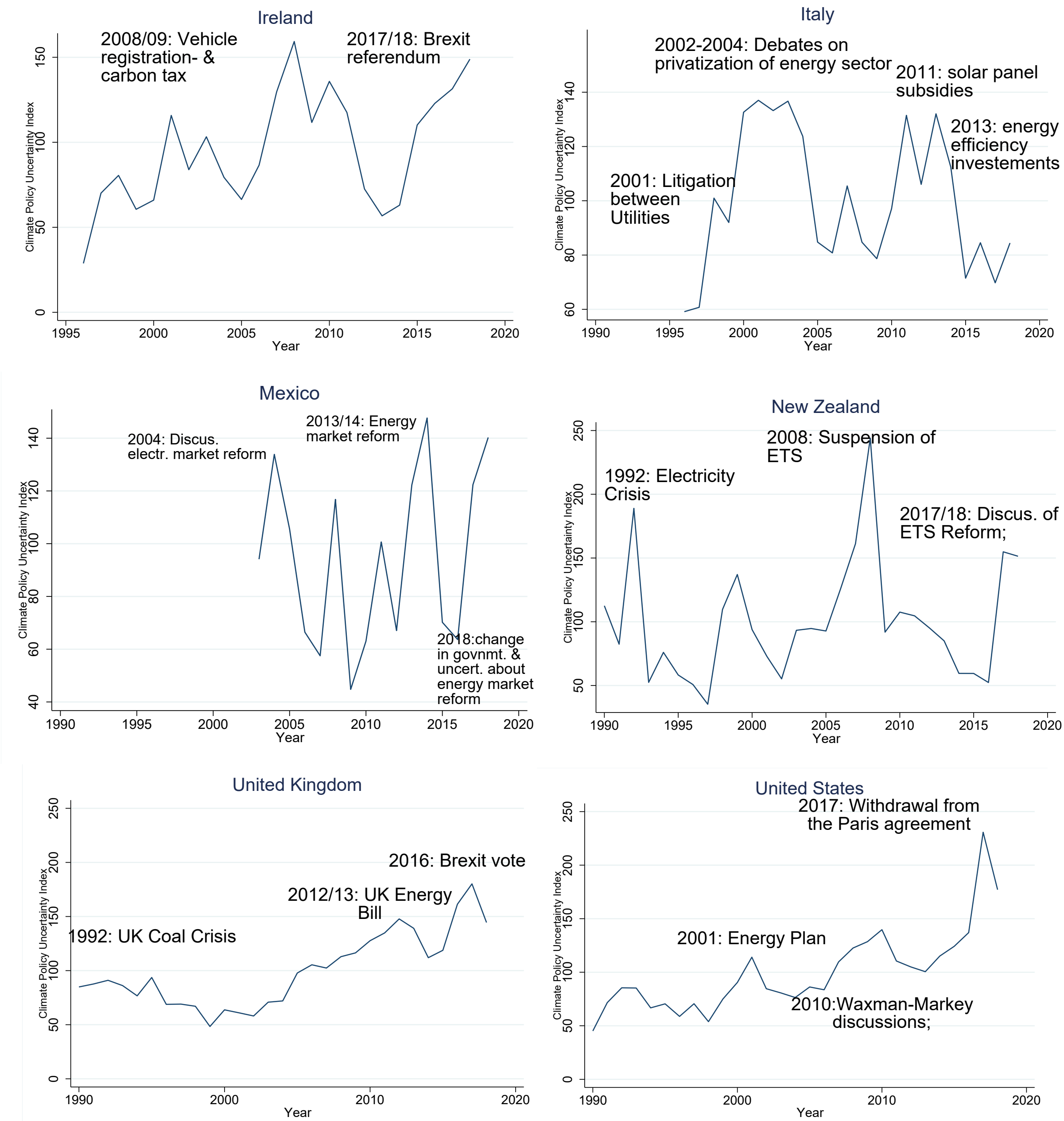
41. The paragraphs below provide more information on the various categories of drivers behind the peaks. Table 2 gives an overview of the different types of policy uncertainty the index captures and illustrates each case with an example.

Figure 3. Country-level index for Climate Policy Uncertainty with associated events (Part 1)



Source: Authors' own calculations based on Factiva/Nexis newspaper data.

Figure 4. Country-level index for Climate Policy Uncertainty with associated events (Part 2)



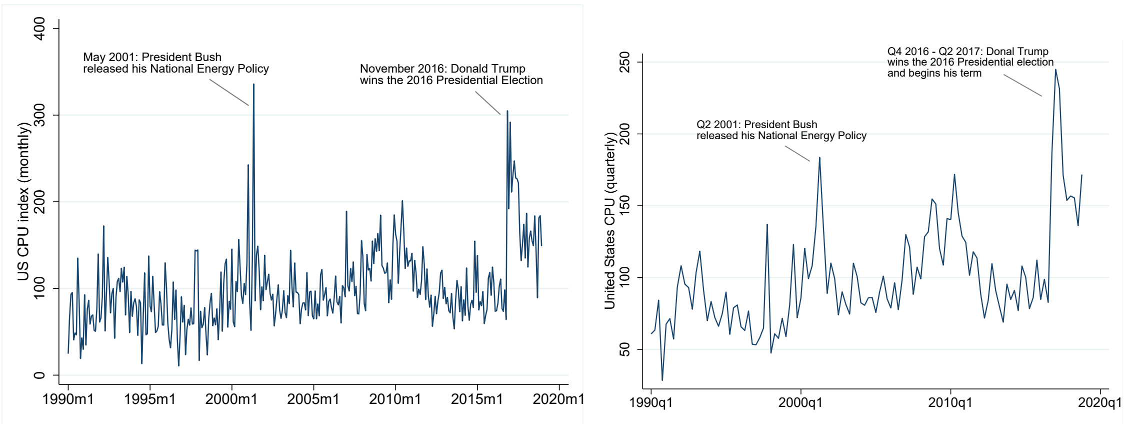
Source: Authors' own calculations based on Factiva/Nexis newspaper data.

42. In addition to the annual time series of the CPU index, the paper also computes higher frequency series at the monthly and quarterly level for France, Germany, the United Kingdom, and 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

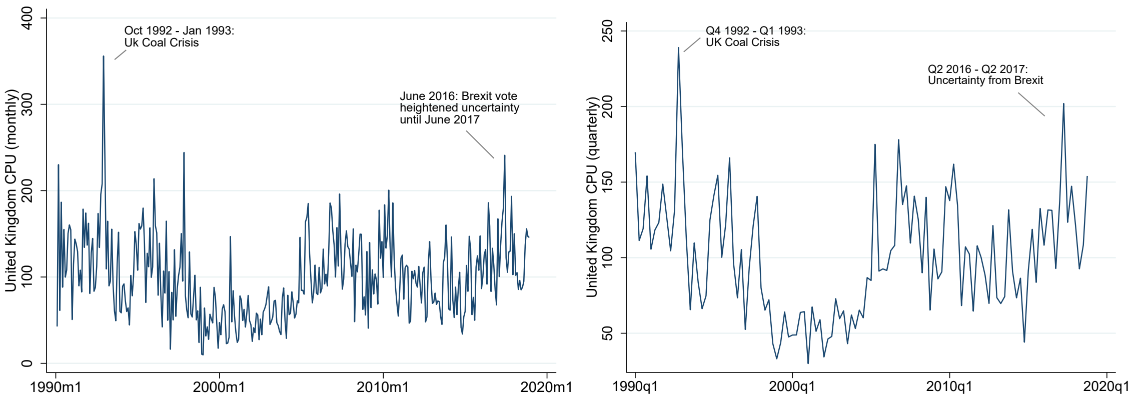
allows examining the variation in the index in more detail (Figure 5). It is, however, important to note that, by design, annual (Figure 3 and Figure 4) and the higher frequency (Figure 5) time series can identify different peaks. Such difference may arise if, for instance, the discussion of a policy 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, while it is more pronounced in the quarterly series. Figure 5 shows elevated levels of climate policy uncertainty throughout 2010. Therefore, the combination of annual and higher frequency time series provides unique insights as it allows analysing all policy events from both perspectives. At high levels of frequency the series can become noisy if the number of CPU articles in a country is low in particular months. There can be a trade-off between frequency and volatility of the index series. Depending on the purpose of use, researchers can choose the appropriate level of frequency.

Figure 5. Higher frequency series for Climate Policy Uncertainty with associated events

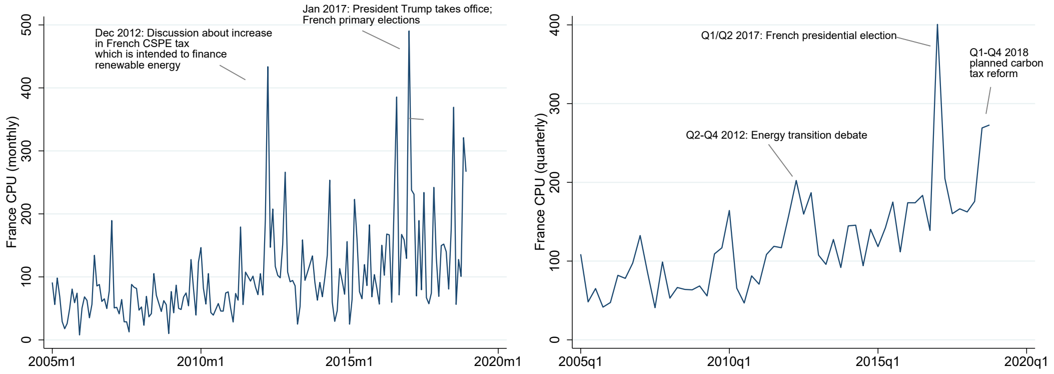
Panel A: United States (monthly and quarterly)



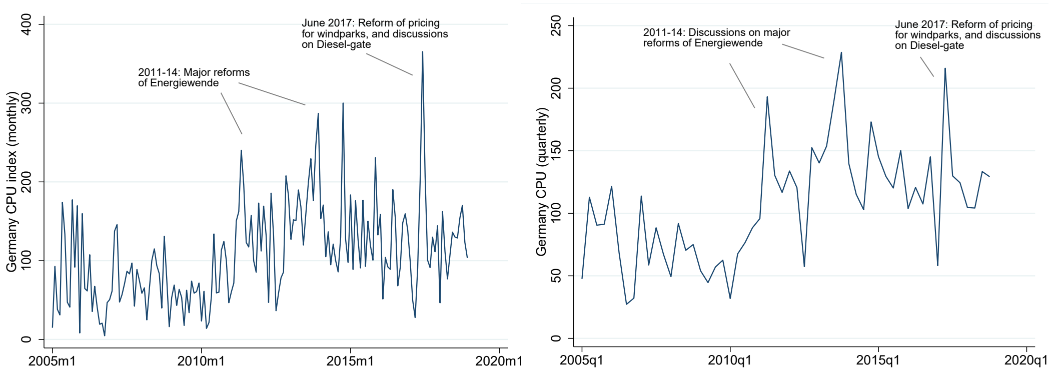
Panel B: United Kingdom (monthly and quarterly)



Panel C: France (monthly and quarterly)



Panel D: Germany (monthly and quarterly)



Note: The figure shows the monthly and quarterly CPU index for the United States, the United Kingdom, France and Germany with a selection of associated events.
Source: Factiva; OECD.

Weakening of climate policies

43. Reading the newspaper articles that are underlying the peaks in the index, we link movements in the index to specific policy events. For Australia and New Zealand, the index peaks when planned emissions trading schemes were either abolished or temporarily suspended, following an election and change in government. In the case of Australia, we observe high levels of CPU between 2012 and 2013 when the planned emissions trading scheme received growing opposition. The ETS was subsequently abolished after a change in government in 2013. In New Zealand, the ETS was temporarily suspended in 2008 after the change in government, driving a peak in the index. The New Zealand ETS was amended and continued in 2009 by the new government, leading to declining levels of CPU.

44. In the United States, the index shows peaks in 2001, 2010 and 2017. The first peak in 2001 is primarily linked to the release of National Energy Policy in May by the Energy Task Force created by the Bush Administration. The 169-page report included environmental deregulation, in particular with respect to oil and gas explorations. The lengthy discussion around the publication of the Plan also contributed to the spike of the index in 2011. In particular, this appears clear when looking at the spike in the monthly index in March, when the National Energy Summit was held. The spike in 2010 is driven

by the Democratic Party withdrawing a major bill on climate change due to insufficient support in Congress. The uncertainty around future climate change regulation in the absence of this bill is driving the spike. 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 related to uncertainty arising from the potential decision, then confirmed, to withdraw from the Paris Agreement and efforts to revoke clean energy and climate policies.

Repeated changes to energy market regulations

45. For Chile and Mexico, the indicator is largely driven by frequent reforms of the energy market. For Chile we observe distinct spikes in 2003/04 and 2014, which are driven by discussions about, and the implementation of, major energy market reforms. The Mexican index shows peaks in 2003, 2013/14, and 2018 that are similarly driven by uncertainty surrounding energy market reforms (note that for Mexico, the article counts identified by our search strategy are lower than for the other countries, making the series relatively volatile).

46. For Spain the spikes of the index in 2009/10 and 2012/13 are also driven by energy sector reforms, which are specific to feed-in tariffs (FIT) for renewables. Concerns emerged that the Spanish FIT were too generous and expensive because the installed capacity grew faster than expected. The concerns about these unsustainably high FITs generated uncertainty because it became unclear how long they could be maintained. The discussions around the reform in 2012/13 increased the level of uncertainty. Following the reform, CPU declined.

47. For Italy we observe elevated periods of CPU around 2011 driven by uncertainty concerning the extension of financial incentives for solar panels, as well as uncertainty from the reorganization and privatization of the energy sector between 2002 and 2004.

48. In Germany, the index shows elevated levels of uncertainty for the years 2011 to 2014, which is largely driven by debates about, and reforms of, the major energy transition laws (‘EEG’) as part of the ‘Energiewende’. With the exception of this period, the German CPU is however relatively flat.

Strengthening of climate policies

49. The peaks of Canada, France and Ireland are largely driven by discussions over reforms that have strengthened climate policy. These include the 2008 introduction of the British Columbia carbon tax in Canada, in France the 2010 environmental law (‘Grenelle de l’environnement’) and the planned carbon tax reform in 2018, and the 2009/10 introduction of the carbon tax in Ireland. The index also shows a similar peak for the United Kingdom in 2012/13, driven by the UK Energy Act. In the case of Canada it is interesting to observe that the introduction of the British Columbia carbon tax generated a much smaller peak than the discussions around the federal carbon tax in 2018, which may be due to the difference in scope of the regulation. We analyse the direction of uncertainty associated with a strengthening or a weakening of policies in further detail below in Section 3.3..

Generalized uncertainty

50. Finally, few spikes in our index are driven by non-environmental uncertainty spikes that have direct implications on climate or energy policies. An example is the United

Kingdom's vote in 2016 to leave the European Union that increased uncertainty in the United Kingdom regarding climate change policies that were previously managed by the EU, and in particular regarding the European carbon market (EU ETS).

Summary

51. Examining the spikes of the index over the past three decades, we observe that CPU is often driven by one of three sources. First, changes in policy direction due to a change in government, or changing political priorities. This uncertainty has generally been associated with dicussions over climate policies being abolished or with withdrawals from climate treaties, rather than from strengthening of climate regulation following elections. A second major driver of uncertainty are frequent changes to climate policies and unclear political positioning that generate elevated levels of uncertainty over longer periods of time. We observe this in the context of energy market regulations, specifically revisions to feed-in tariffs for renewable energy production. Third, uncertainty spikes with debates surrounding the stringency and scope of new climate policies. Depending on the planned ambition of the policy and opposition against it, the uncertainty can be focussed on relatively short periods of time, or may extend over multiple years. The underlying direction of the uncertainty is further explored by leveraging on the two alternative sub-indices that capture accelerations in the transition towards a cleaner economy and decelerations from a weakening in climate policy in the next section. Finally, few spikes in the index are driven by non-climate uncertainty with direct implications on climate or energy policies (see Table 2 for examples).

Table 2. Types of Climate Policy Uncertainty

Category of uncertainty	Type of climate policy uncertainty	Examples
Discussions over weakening of climate regulation	Reversal of or withdrawal from climate policies.	Australia abolishes carbon pricing in 2013/14.
	Lowering of existing climate or energy policy standards.	The 2001 United States Energy Plan, which set incentives for increased exploration of oil and gas fields.
Potential introduction or strengthening of climate regulation	Introduction of new climate regulation.	The 2008 introduction of a carbon tax in British Columbia.
	Strengthening of existing climate regulation.	Parts of the German EEG law (Energiewende) reform between 2011-2014.
Unexptected and/or repeated changes to policies	Frequent changes to energy market reforms.	Concerns about unsustainably high FITs in Spain in 2009/10 and the reform of FITs in 2012/2013.
General uncertainty	Climate Policy Uncertainty arising from non climate-specific policy decisions.	The United Kingdom's vote in 2016 to leave the European Union. It raised uncertainty concerning firms regulated within the EU ETS, as well as concerns on future UK energy security.

Source: Authors.

3.3. CPU and Alternative Indicators

52. To assess the sensitivity of the indicator, we construct alternative versions of the index (see Box 2 for a detailed description of the alternative indicators). First, we construct an alternative index for business newspapers only. This is based on the assumption that business newspapers may be more likely read by the business community and therefore more likely to potentially influence investment decisions. The alternative index based on business newspapers is very similar to our baseline index. Figure B.1 in Annex B shows the business index for countries where data is available on the major business newspaper. It is used in some of the robustness checks in the empirical analysis presented in Section 4.

53. Second, we want to ensure that the index is not simply driven by growing environmental concerns and awareness. A concern is that as environmental awareness has grown over the last three decades, the number of articles on climate change topics (including on climate policies) has also increased over time at a pace which might be different from the total number of articles published on all subjects. We therefore construct two alternative versions of the index which control for increased interest in environmental topics and policy (see Box 2 for further details). The alternative indicators obtained from these specifications are highly correlated with the baseline index which uses total newspaper article count as the denominator. Figure C.1. and Figure C.2. in Annex C present these alternative indicators for all countries.

54. These alternative indicators strengthen our confidence that the index is not driven by the choice of individual newspapers, and that it is driven by country-specific climate policy uncertainty and not just growing environmental concerns and awareness.

55. Third, we run an additional newspaper article search exclusively restricted to keywords related to climate policy. By doing so, we can investigate whether the differences in topical scope between the original and the restricted version of the indicator alter the observed uncertainty trends in our baseline indicator to a considerable degree. The rationale is to verify whether variations in our index are fundamentally driven by uncertainty about policy developments targeting other environmental concerns related to more local issues than climate regulation, a global public good. Figure B.2 in Annex B plots the index resulting from the narrower search for the United States (which we denote as N-CPU where the "N" stands for narrow) and compares it to our original indicator. Overall, they exhibit a correlation of 0.9974, suggesting that observed shocks in our index are ultimately driven by uncertainty related to policies addressing climate change. Annex A provides more detail about the search strategy used to compute N-CPU.

56. Finally, we established two alternative sub-indices, adding keywords related to progress and failure, respectively, to the original keyword search. As discussed in Section 3.2, greater climate policy uncertainty can be driven by different sources (see Table 2). In particular, uncertainty about climate policy developments may either point to additional delays in climate action or expectations of more stringent regulation in the future. Indeed, the process of implementing climate policy has had many instances of acceleration and deceleration. Hence, it is important not only to analyse variations in the CPU index over time, but also try to disentangle its drivers: whether an increase in uncertainty suggests that the transition is slowing or accelerating. We denote the resulting sub-indices as CPU+ ("CPU plus") when belief revision goes towards more climate action or a strengthening of climate policy, and CPU- ("CPU minus") when belief revision goes towards less climate action or a weakening of climate policy. Figure 6 plots the evolution of the sub-indices for English speaking countries over time, linking respective index-specific peaks to policy-

relevant events. We compute the sub-indices at the annual level because of the trade-off between frequency and volatility of the indices. For the sub-indices the number of articles discussing a weakening or strengthening of climate policies becomes smaller which increases the volatility in the indices further. The keyword searches for CPU+ and CPU- can be found in Appendix A.

57. Panel A of Figure 6 plots the CPU- (left panel) and CPU+ (right panel) for the United States showing that the uncertainty surrounding the plan by the United States to withdraw from the Paris Agreement leads to a pronounced spike in CPU- in 2017, but is less pronounced in CPU+, which it is driven by sub-national initiatives to try to increase policy stringency following the announced withdrawal from the Paris Agreement. For the United Kingdom the spike following the Brexit referendum is more pronounced in CPU- due to concerns that leaving the EU ETS would imply a weakening of national climate policy. For Canada we observe a pronounced peak in CPU- in 2018 that is driven by Ontario moving to repeal its cap-and-trade programme. The Australian CPU+ has spikes in 2008 when political discussions about an Australian ETS emerge and in 2011, when the Australian ETS regulation is temporarily passed, but the Australian CPU+ declines subsequently as the momentum vanishes, as the ETS regulation is eventually dismantled. Consistently, the Australian CPU- is at high levels between 2011-13 because of the uncertainty and eventual dismantling of the Australian ETS.

Box 1. Alternative Indicators

The baseline index uses several newspapers in each country with a view to ensuring representativeness and to limit volatility. However, a potential concern with this approach is that the business community may turn primarily to business newspapers for information likely to impact business decisions, rather than to the general press. To tackle this issue, an alternative option is to focus on business newspapers only, which are more likely to be read by and hence to influence the business community, and to report on policy changes subject to influence the business community.

The alternative “business newspaper” indicator is based only on the main business newspaper in each country. This restricted indicator produces a very similar pattern to the baseline indicator across countries and is used in some of the robustness checks in the empirical analysis presented in Section 4. Figure B.1 in Annex B shows the business index for countries where data is available on the major business newspaper.

Another potential concern is that as environmental awareness has grown over the last three decades, the number of articles on climate change topics (including on climate policies) has also increased over time at a pace which might be different from the total number of articles published on all subjects. Therefore, dividing the number of Climate Policy Uncertainty articles by the number of total articles might lead us to partly capture general environmental concerns rather than only uncertainty coming from new policies.

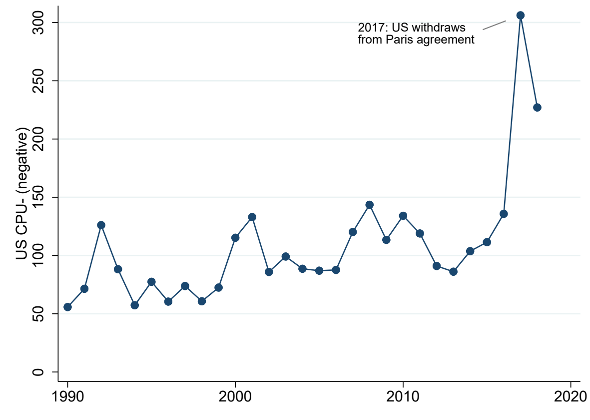
In order to analyse the sensitivity of the indicator to the choice of the denominator, two alternative version of the index are created aimed at controlling for an enhanced interest in climate topics and policy. In these alternative indicators, the number of articles concerning climate policy uncertainty are respectively divided by (i) the number of articles concerning the climate or (ii) the number of articles concerning climate policy. These alternative denominators are created by counting articles picked up respectively by the first part of the search strategy (the "climate" bracket) and by the first and second part of the search strategy (the "climate" and "policy" brackets).

For most countries, the alternative indicators obtained from these specifications are highly correlated with the baseline index which uses total newspaper article count as the denominator. Annex C presents these alternative indicators for all countries.

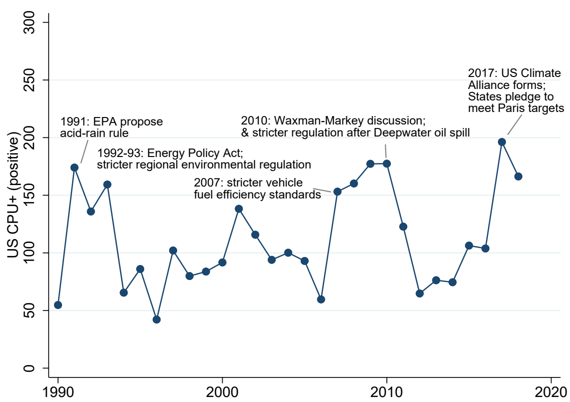
Figure 6. Annual series of CPU- (weakening of climate policy) and CPU+ (strengthening of climate policy)

Panel A: United States

CPU- (left panel)

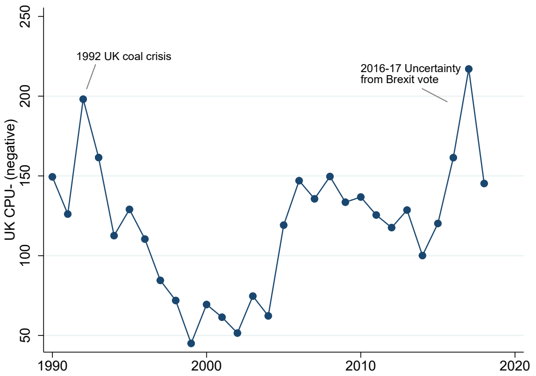


CPU+ (right panel)

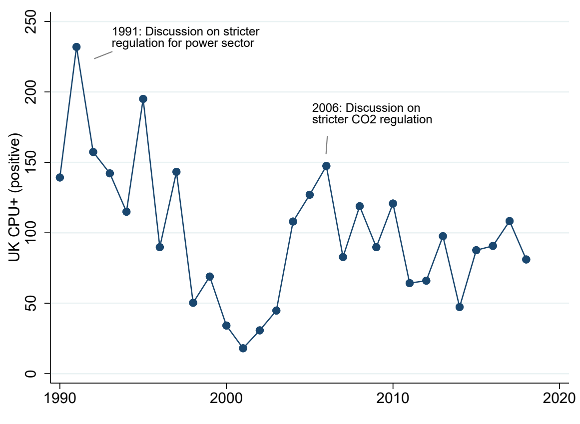


Panel B: United Kingdom

CPU- (left panel)

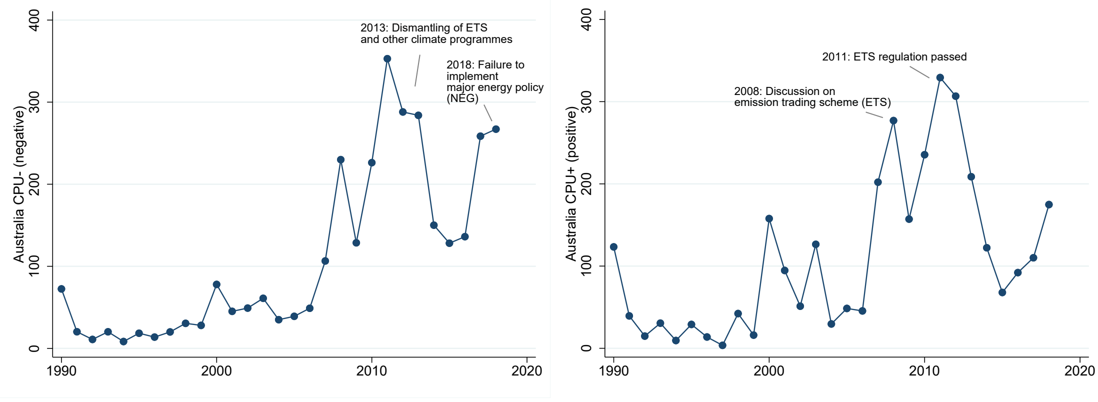


CPU+ (right panel)



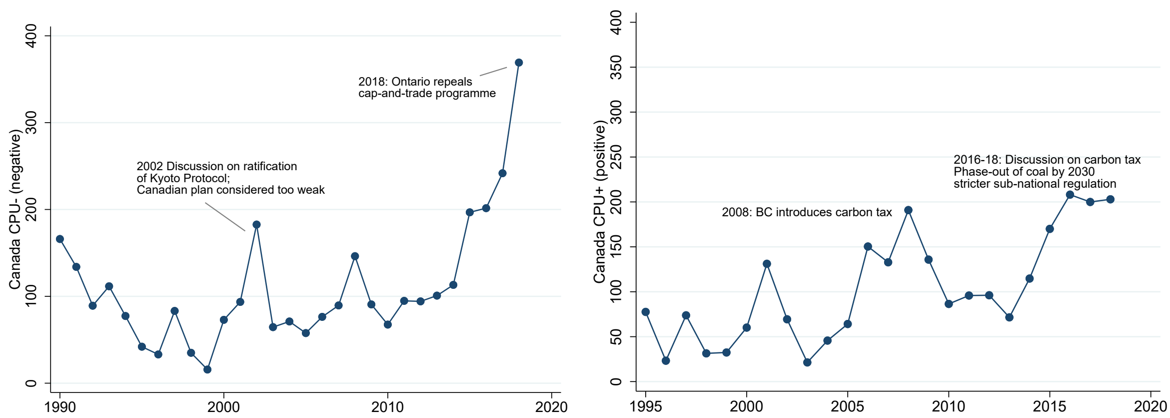
Panel C: Australia

CPU- (left panel) CPU+ (right panel)



Panel D: Canada

CPU- (left panel) CPU+ (right panel)



Note: The Figure shows the annual series of CPU- (less climate policy action) and CPU+ (more climate policy action) for English speaking countries.
Source: Factiva; OECD.

3.4. CPU, Economic Policy Uncertainty and Environmental Policy Stringency

58. The OECD's CPU indicator is the first of its kind, making it impossible to compare it with a readily-available benchmark. The most closely related indicator that the CPU index can be compared with is the Political Risk indicator developed by Hassan et al. (2019[47]). The authors construct a firm-specific index of political risk for more than 7000 listed firms in the United States between 2002 and 2016. They use quarterly "earnings conference calls" – a common communication channel for listed firms – to create an index that captures the share of earnings conference calls devoted to discussing political risk. In addition to their overall indicator, they also decompose overall political risk by topic and generate an environmental political risk indicator, which we compare with the US indicator

of Climate Policy Uncertainty. We observe broad correlation between their index and CPU, and peaks in the same periods (see Annex D).

59. Next, we compare the CPU index against two potential confounders: the Economic Policy Uncertainty indicator developed by Baker, Bloom and Davis (2016[12]), and the OECD's Environmental Policy Stringency indicator (Botta and Koźluk, 2014[45]). This addresses two potential concerns. First, the Climate Policy Uncertainty indicator might pick up general policy uncertainty (associated, for example, with political cycles), in which case a strong correlation with Economic Policy Uncertainty could be expected. Second, Climate Policy Uncertainty could merely capture variation in environmental policy stringency, with peaks in both cases associated with major increases in policy ambition.

60. Annex F plots the CPU Index against the Economic Policy Uncertainty Index (EcoPU) by Baker, Bloom and Davis (2016[12]) for each country. The two indices show the overall rising levels of both EcoPU and CPU as documented by Baker, Bloom and Davis (2016[12]). It also shows pronounced differences, in particular as regards individual spikes of the index, suggesting that the CPU indicator is a distinct component within general policy uncertainty. In the United States for example, the last presidential election had a markedly higher impact on climate policy uncertainty than on economic policy uncertainty. Conversely, the United Kingdom's vote in 2016 to leave the European Union had a much larger impact on economic policy uncertainty than on climate policy uncertainty while the major discussions in Germany over the energy transition law ("Energiewende") are completely specific to climate policy and did not translate into a higher economic policy uncertainty (see Annex F).

61. In general across the 12 countries, changes in CPU over time are only weakly associated with changes in EcoPU. The correlation coefficient between within-country yearly changes in CPU and in EcoPU is 0.16 (see Figure E.1. in Appendix E). While the EcoPU index is largely dominated by macro-economic crises, wars, and oil shocks, the CPU is driven largely by uncertainty surrounding specific climate policies. The observed differences in the indicators of economic vs climate policy uncertainty suggest that the CPU indicator is specific to climate policy.

62. A different concern might be that the climate policy uncertainty indicator merely captures variation in environmental policy stringency. Therefore, we compare the CPU Index against the OECD Environmental Policy Stringency (EPS) indicator developed by Botta and Koźluk (2014[45]). Annex G presents the time series of CPU against EPS for each country, and shows different trends across the two indices. In order to systematically compare the evolution of CPU with that of EPS, we again calculate the correlation coefficient between within-country yearly changes in CPU and in EPS. The association is even weaker than between CPU and EcoPU, with a correlation of 0.04. This very low correlation provides evidence that the CPU index captures additional variation beyond Environmental Policy Stringency (see Figure E.2 in Appendix E).

4. Empirical application: The impact of Climate Policy Uncertainty on Firm Investment

63. Having established the validity of the CPU indicator, this section turns to investigating the effects of climate policy uncertainty on firm investment. The analysis uses firm-level data and relies on within-country variation of climate policy uncertainty over time combined with cross-sector variation in exposure to climate policy uncertainty to provide causal evidence on the effect. Cross-country variation in the level of CPU at a given

point in time is *not* used for the identification for the reasons explained above. A companion paper (Basaglia et al., forthcoming[48]), focuses on the United States and provides empirical analyses, including at the quarterly level, on a wide range of firm-level outcomes, while also analyzing specifically the role of CPU+, CPU- and N-CPU.

4.1. Identification Strategy

64. Regressing firm-level investment on country-level climate policy uncertainty does not provide a credible identification strategy, as country-specific CPU might be correlated with multiple country-level omitted variables such as macroeconomic conditions, economic policy uncertainty or other policy changes. A more credible setting would include using country-year fixed effects to control for any such unobserved variables at the country-year level. In order to allow for the inclusion of country-year fixed effects, the identification strategy relies on sectors' exposure to climate policy uncertainty to create variation in climate policy uncertainty at the country-sector-year level. This approach is similar to that of Baker, Bloom and Davis (2016[12]), who use sector-level share of firms' revenue coming from federal purchase of goods and services as a measure of sectors' exposure to economic policy uncertainty.

65. The degree of exposure to climate policy uncertainty is proxied by CO_2-intensity at the country-sector level (defined at the NACE 2-digit level). Since CPU focuses on climate policies, CO_2 intensity should provide a good proxy for exposure to climate policy uncertainty. To mitigate concerns over reverse causality and smooth out yearly variation in CO_2 intensity, average CO_2 intensity over the period 2005-2015 is used to generate exposure for each 2-digit NACE sector in each country. Using a time-varying CO_2-intensity at the sector level could raise potential endogeneity concerns. For example, if investment by a large firm in a given sector influences CO_2 intensity in that sector, the regression would suffer from reverse causality.

66. An important advantage of interacting our explanatory variable of interest (CPU) with CO_2 intensity is that it greatly reduces concerns of omitted variable bias in our estimation. Indeed, any omitted variable would only pose a problem if its effect was similarly mediated by (and in proportion to) CO_2 intensity. It is difficult to think of such variables with the exception of environmental policy stringency and climate policy uncertainty.

67. To control for any potential bias coming from the correlation between climate policy uncertainty and the level of environmental policy stringency, we include the EPS indicator in all regressions, also interacted with country-sector-level CO_2 intensity in order to obtain a measure of policy stringency at the country-sector-year level.

68. In order to eliminate any bias that would be generated by a correlation between time-invariant firm characteristics (likely to affect current and future investment) and the level of the climate policy uncertainty shock, we estimate an equation in first-differences. Thus, the change in investment is regressed on the change in CPU and on the change in EPS (both interacted with exposure).

69. As we have no presumption regarding the timing of the investment response to climate policy uncertainty shocks, we include both the contemporaneous shock as well as the lag for the CPU variable in our baseline regressions, which we include one by one. In robustness checks presented below, we also include further lags as well as a full set of leads for the CPU shocks in order to address concerns of the potential presence of reverse

causality, which is further discussed below in the robustness checks. We verify that the response of investment to future shocks remains insignificant.

70. Therefore, the baseline equation we estimate takes the following form:

$$\Delta\log\left(I_{it}\right) = \sum_{k=0}^{1}\left[\alpha_k \Delta \log\left(CPU_{c,t-k}\right) \times \log\left(CO2\ int_{cs}\right) + \gamma_k \Delta \log\left(EPS_{c,t-k}\right) \times \log\left(CO2\ int_{cs}\right)\right] + \delta_{ct} + \varepsilon_{it} \qquad (1)$$

where *i* stands for firm, *s* for sector, *c* for country and *t* for year.

71. In all regressions, the coefficients are weighted by the square root of the average investment of the firm over the sample period.[5] Since there are many more small than large firms, not weighting the coefficients would capture the impact of climate policy uncertainty on the average firm (which is small, as the median firm in the sample has 12 employees) rather than the average impact on investment at the aggregate level. In the heterogeneity analyses presented below, unweighted regressions are ran on different samples according to firm size.

4.2. Data sources and descriptive statistics

72. To measure climate policy uncertainty, we use the index presented above. Other data sources are detailed below. Table G.1 in Annex G reports the descriptive statistics.

4.2.1. Investment and the ORBIS database

73. We rely on the private financial and economic database Orbis to obtain cross-country firm-level data on investment. Sorbe, Gal and Millot (2018[49]) and Gal and Hijzen (2016[50]) describe the different steps of the cleaning procedure implemented to obtain the "enhanced" version of the database in use at the OECD. The analysis uses unconsolidated accounts of firms in order to keep separate entries for national subsidiaries. We use unconsolidated accounts specifically to ensure that firms are primarily exposed to the policy uncertainty in the country in which they are located (multinational firms are likely to be affected by CPU across the countries in which they operate). The coverage of the Orbis database spans the entire period of the climate policy uncertainty index, from 1990 to 2018.

74. The analysis focuses on the mining, manufacturing, utilities, and construction sectors (NACE classification sections B to F, or 2-digits sectors from 05 to 43). Other sectors (such as retail trade, accommodation, financial and insurance services) are typically not subject to climate and air pollution policies. The working dataset consists in a panel of around 430,000 unique firms for the countries covered by the Climate Policy Uncertainty index.

75. Following Sorbe and Johansson (2017[51]), firm investment is defined as:

$$I_t = FixedAssets_t - FixedAssets_{t-1} + Depreciation\ and\ Amortization \qquad (2)$$

Netting for depreciation implies that the numerator of this measure corresponds only to the new fixed assets created or bought by the firm in year *t*. This is because both fixed assets

[5] Weighting by average investment does not change the magnitude of the coefficients, but affects precision – a well-known issue when some weights are particularly large (Solon, Haider and Wooldridge, 2015[62]).

and depreciation are measured at book value and thus consistent with each other in the ORBIS database.

76. It is important to highlight some caveats related to the use of Orbis. First, the coverage of firms varies substantially across countries with almost full coverage in countries such as Italy and Spain and very limited coverage of countries such as the United States (Bajgar et al., 2020[52]). Second, the firm population in Orbis is not representative, but biased towards listed firms that are typically larger, older and more productive. In countries with good coverage (mostly in Europe), firms included in Orbis represent around 40% of the firm population.

4.2.2. CO_2 Intensity

77. We use a country-sector-year dataset of CO_2-intensity constructed by the International Energy Agency (IEA) and the OECD. The data covers 65 economies, 36 industries over the years 2005-2015, providing to our knowledge the most detailed sector-level and comprehensive cross-country dataset on CO_2-emissions intensity (Yamano and Guilhoto, forthcoming[53]). CO_2-intensity is measured in tonnes of CO_2 per million USD of value added. The dataset uses the OECD ANBERD (Analytical Business Enterprise Research and Development) sector classification, which is roughly at the 2-digit ISIC level, but for some sectors groups several 2-digit industries together (e.g. ISIC 05 and ISIC 06, are grouped into a single industry group). Based on this data we compute the country-sector average CO_2-intensity over the available time period (2005-2015).

4.2.3. Environmental Policy Stringency (EPS)

78. Information about environmental policy stringency comes from OECD's EPS indicator (OECD, 2019[54]). The EPS covers almost all OECD and G20 countries over the period 1990 - 2015. It combines information on 14 market-based and non-market-based policy instruments, regulating primarily CO_2 and other air pollutants in the energy and transport sectors. All regulations are aggregated into a single indicator at the country level. The EPS is positively correlated with survey-based measures of perceptions of environmental policy stringency (Botta and Kozluk, 2014[55]) and with energy price indices at the country level (Garsous and Kozluk, 2017[56]). The EPS index exists for all countries in our sample except New Zealand and Chile and spans the period 1990-2015 for the majority of countries.

4.3. Results

4.3.1. Main results

79. Table 3 shows the results of estimating Equation (1). Columns (1) and (2) report the results for the baseline equation, while columns (3) and (4) add firm-specific trends to account for potential differential trends in investment between firms. Columns (1) and (3) include contemporaneous CPU while columns (2) and (4) add lagged CPU. Standard errors are conservatively clustered at the country-sector level rather than at firm level to account for potential error correlation not only within firms across time but also across firms operating in the same country and sector.

80. The results show that higher climate policy uncertainty has a statistically significant and negative impact on firm investment. A 10% increase in CPU for the average exposed firm decreases investment by about 2-3% in year *t*. The impact in year *t*+1 is statistically significant in column 2 (at slightly less than a 2% decrease) but not robust to the inclusion

of firm trends, so we conclude that the effect is strongest and highly statistically significant mostly in the year when the uncertainty shock occurs. The results presented in the next subsection show that the effect totally dissipates in year *t*+2.

81. It is interesting to note that the most demanding specifications (columns 3 and 4) show a positive and statistically significant effect (at the 10% level) of Environmental Policy Stringency on investment, consistent with the idea that increases in EPS induce firms to invest in novel production equipment (Dlugosch and Kozluk, 2017[57]; Garsous and Kozluk, 2017[56]).

82. Overall, these results support our initial hypothesis that climate policy uncertainty negatively influences investment, in line with theoretical predictions (Bernanke, 1983[6]; Pindyck, 1988[8]; Bretschger and Soretz, 2018[13]; Fried, Novan and Peterman, 2020[14]; Dixit and Pindyck, 1994[9]). Similar findings were shown for economic policy uncertainty (Baker, Bloom and Davis, 2016[12]), but this study is the first to provide empirical evidence of the impact of climate policy uncertainty specifically.

Table 3. Baseline Results

	(1)	(2)	(3)	(4)
Dep. Var.	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)
Δ log(CPU)$_t$ X log(CO_2 int)	-0.0270***	-0.0320***	-0.0188**	-0.0225***
	(0.00966)	(0.00953)	(0.00851)	(0.00868)
Δ log(CPU)$_{t-1}$ X log(CO_2 int)		-0.0181**		-0.00905
		(0.00903)		(0.00945)
Δ log(EPS)$_t$ X log(CO_2 int)	0.0195	0.0215	0.0500*	0.0501*
	(0.0295)	(0.0297)	(0.0277)	(0.0269)
Δ log(EPS)$_{t-1}$ X log(CO_2 int)		-0.0139		0.0171
		(0.0257)		(0.0241)
Country-year fixed effects	yes	yes	yes	yes
Firm time trends	no	no	yes	yes
N	2283131	2283131	2277406	2277406
Number of firms	438901	438901	436665	436665

Note: The dependent variable is investment as defined by equation (2). All columns estimated by OLS. Standard errors clustered at country-sector level in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

83. To assess the magnitude of the estimated impact of climate policy uncertainty on investment, we measure the one-year change in investment implied by our coefficient for respectively firms with low and high carbon intensity. Recall that the identification strategy exploits exposure to climate policy uncertainty as measured by log CO_2 intensity, so the effects varies by construction according to CO_2 intensity. Table 4 presents the implied impact for a typical increase in CPU of one standard deviation (+37 points from the mean of 100) and for a larger increase of two standard deviations (+74 points). A 74 points increase corresponds to a large shock such as the run-up in the United Kingdom to the 2016 referendum to leave the European Union, but is not an extreme outlier. For example, the discussions on the introduction of a federal carbon price in Canada, on new climate policies in France following the Paris Agreement, on the Energiewende in Germany, or on reforming the ETS in New Zealand, all led to increases of the CPU index by over 100 points.

84. For a firm with a median carbon intensity (243 tons of carbon per million USD of value added)[6], and using the conservative estimate reported in column 4 of Table 3 for the contemporaneous effect (-0.0225), a one standard deviation increase in CPU (+37 points) implies a one-time investment drop of 3.8% (= 1 – exp(ln(1.37) * ln(243) * 0.0225)). But for a high carbon intensity firm (2394 tonnes of carbon per million USD of value added, which corresponds to the average intensity in the rubber and plastic, oil and natural gas extraction or coke and refined petroleum sectors), a large but not atypical rise in CPU (+74 points) decreases investment by 9.2%. Hence, for firms with high exposure to climate policy, the estimates imply that swings in policy uncertainty involve significant reductions in investment.

Table 4. Magnitude

		Change in CPU	
		Typical (1 s.d.)	Large (2 s.d.)
CO_2 intensity	Low (median)	-3.8%	-6.6%
	High (90th percentile)	-5.4%	-9.2%

Note: A one standard deviation increase in CPU is a +37 points increase from a mean of 100 in each country. 2 standard deviations is a +74 points increase. The median CO_2 intensity is 243 tons/Million USD of value added. The 90th percentile of the CO_2 intensity distribution is 2394 tons/Million USD of value added.

4.3.2. Robustness

85. We conducted a series of sensitivity analyses to verify the robustness of the baseline findings.

Reverse causality concerns

86. Probably the main econometric concern with this empirical setting is the potential presence of reverse causality. For example, if a polluting sector is growing (increasing investment), this might attract the attention of the government and generate discussions in the press over the necessity to regulate this sector's emissions, leading to an increase in climate policy uncertainty. Symmetrically, if a sector is experiencing difficulties (decreasing investment), this might generate discussions over the potential benefits of lowering environmental policy stringency in that sector. In those examples, the outcome variable (the change in investment) causes climate policy uncertainty rather than the opposite, creating endogeneity.[7]

87. If this type of reverse causality is at play, we would expect *future* climate policy uncertainty to be correlated with contemporaneous investments. To make sure that reverse causality is not at play, we estimate equation (1) above but include a set of leads for the CPU variable in order to verify that the response of investment to future shocks remains

[6] This corresponds to the median CO2 intensity for sectors included in the analysis, i.e. NACE codes up to 43 (groups B-F of the NACE classification Rev. 2).

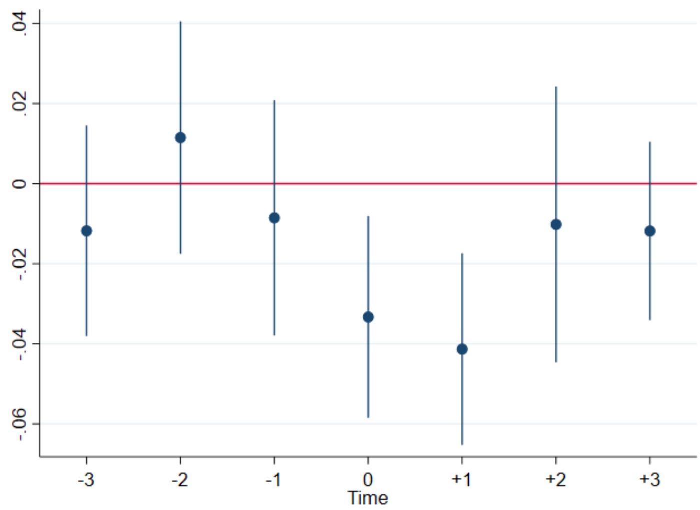
[7] This concern is related to the literature on endogenous coverage of news and its relationship with policy (Sen and Yildirim, 2015[60]; Mullainathan and Shleifer, 2005[61]), which argues that news coverage may be driven by readers' interest in the topic.

insignificant (see Aghion et al., (2018[58])), for a recent application of this method). We include a total of 3 lags, 3 leads and the contemporaneous shock.[8] We thus test the following specification:

$$\Delta\log(I_{it}) = \sum_{k=-3}^{3}[\alpha_k \Delta\log(CPU_{c,t-k}) \times \log(CO2\ int_{cs}) + \gamma_k \Delta\log(EPS_{c,t-k}) \times \log(CO2\ int_{cs})] + \delta_{ct} + \varepsilon_{it} \quad (3)$$

88. If there is no reverse causality, the α_k coefficients for k < 0 should be insignificant. The results for the α_k coefficients and their associated 95% confidence intervals are represented graphically in Figure 5 for k = −3,...,3. The coefficients are unsurprisingly noisily estimated due to multicolinearity between covariates, but despite this, we still observe a strongly statistically significant effect of CPU on investment only in years *t* and *t*+1 (in line with the baseline results presented above). Most importantly for our identification strategy, none of the pre-trend coefficients (k < 0) are significant. This provides reassurance that the model is able to recover the causal effect of CPU on investment rather than the opposite. The results in Figure 5 additionally show that all effects of CPU dissipate after two years, when they become close to zero and statistically insignificant.

Figure 7. Distributed Lag Model



Note: Coefficient estimates α_k from the distributed lag model equation (dots) and associated 95% confidence intervals (bars). The x-axis represents time from the CPU shock. Robust standard errors clustered at the country-sector level. The equation is estimated in first-differences and includes a full set of lags and leads of EPS interacted with CO_2 intensity as well as country-year fixed effects.

Investment rate

89. As an alternative to investment (I_t), we use the investment rate, defined as I_t/K_{t-1} = I_t/Fixed_assets$_{t-1}$. As explained by Sorbe and Johansson (2017[51]), a problem with the investment rate calculated from Orbis – which does not provide information on Net Plant,

[8] We have experimented with longer and shorter windows; this does not qualitatively affect our results.

Property and Equipment, used for example by Baker, Bloom and Davis (2016[12]) – is that book value depreciation is generally more rapid than economic depreciation. This means that the denominator ($Fixed\_assets_{t-1}$) is generally lower than the economic value of the capital stock, which results in an upwards distortion in the investment rate. Therefore, I_t is our preferred measure of investment in the baseline regressions.

90. Table 5 reports the results when using the investment rate as an alternative dependent variable. The baseline findings are robust to this measure. In terms of magnitude, the coefficient in column 4 implies that, for a high carbon intensity firm, a large (two standard deviations) rise in CPU decreases the investment rate by 8.8%, very close to the magnitude found for the baseline estimations. Environmental policy stringency also has a statistically positive effect on the investment rate, in line with previous work (Dlugosch and Kozluk, 2017[57]; Garsous and Kozluk, 2017[56])[9].

Table 5. Investment rate as an alternative dependent variable

	(1)	(2)	(4)	(4)
Dep. Var.	Δ log(I_t/K_{t-1})	Δ log(I_t/K_{t-1})	Δ log(I_t/K_{t-1})	Δ log(I_t/K_{t-1})
Δ log(CPU)$_t$ X log(CO_2 int)	-0.0136*	-0.0156**	-0.0183**	-0.0215**
	(0.00762)	(0.00757)	(0.00921)	(0.00955)
Δ log(CPU)$_{t-1}$ X log(CO_2 int)		-0.00441		-0.00761
		(0.00916)		(0.0109)
Δ log(EPS)$_t$ X log(CO_2 int)	0.0529**	0.0506**	0.0573**	0.0578**
	(0.0235)	(0.0251)	(0.0278)	(0.0268)
Δ log(EPS)$_{t-1}$ X log(CO_2 int)		0.0188		0.0203
		(0.0211)		(0.0261)
Country-year fixed effects	yes	yes	yes	yes
Firm time trends	no	no	yes	yes
N	2283131	2283131	2272088	2272088
Number of firms	438901	438901	436665	436665

Note: All columns estimated by OLS. Standard errors clustered at country-sector level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Alternative CPU indices

91. We conducted a series of robustness checks using the alternative specifications of the CPU index described in Box 2. Specifically, the baseline CPU indicator is replaced by (i) the index computed by scaling CPU articles by articles related to the environment; (ii) the index computed by scaling CPU articles by environmental policy articles; and (iii) the index computed based solely on business newspapers in countries where we were able to collect such data.

92. Table 6 shows the results using these CPU indicators. All columns return a negative and statistically significant coefficient which is not statistically different from the baseline. The elasticities vary from 1.8% to 4.0%, but even the smallest coefficient found for the index based solely on business newspapers (column 3) implies a 7.4% drop in investment

[9] Specifically, Table A2.1. of Dlugosch and Koźluk (2017[57]) shows positive and significant effects on the interaction of energy intensity and energy price inflation at t-1 in their model with investment rate as the dependent variable.

following a two standard deviations increase in CPU for high carbon intensity firms, which is still a sizable effect and close to the baseline estimate.

Table 6. Robustness Checks: Alternative Indices

	(1)	(2)	(3)
Indicator	Climate Articles	Climate Pol. Articles	Business newspapers
Dep. var.	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)
Δ log(CPU)$_t$ X log(CO_2 int)	-0.0404***	-0.0238**	-0.0180**
	(0.0110)	(0.0107)	(0.00824)
Δ log(CPU)$_{t-1}$ x log(CO_2 int)	-0.0155*	-0.00920	0.000211
	(0.00888)	(0.00986)	(0.00845)
Δ log(EPS)$_t$ X log(CO_2 int)	0.00982	0.0212	0.00648
	(0.0305)	(0.0293)	(0.0313)
Δ log(EPS)$_{t-1}$ X log(CO_2 int)	-0.0144	-0.0185	0.00461
	(0.0256)	(0.0260)	(0.0272)
N	2283131	2283131	2046286
Country-year dummies	yes	yes	yes

Note: Columns (1) presents baseline specification results using an alternative version of the index where articles mentioning the climate make up the denominator of the index. Column (2) presents baseline specification results using an alternative version of the index where articles talking about climate policy make up the denominator of the index. Columns (3) presents baseline specification results using an alternative version of the index where only business newspapers are used to compute the index. Section 3.3 presents the construction of these alternative indexes in more detail. All columns estimated by OLS. Standard errors clustered at country-sector level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Controlling for EcoPU

93. Additionally, one may be concerned that the effects might not be driven specifically by climate policy uncertainty, but more broadly by overall policy uncertainty. Note that this would only be a concern if the impact of overall policy uncertainty had a differential impact on firms depending on their CO_2 intensity (the impact of overall policy uncertainty is already controlled for through the inclusion of country-year fixed effects). It is hard to think that this would be the case, but it could be if CO_2 intensity was correlated with other measures of policy exposure at the firm level.

94. We lack a measure of overall policy uncertainty, but can control for economic policy uncertainty, which is undoubtedly a major component of overall policy uncertainty. To control for EcoPU, we take three separate approaches. First, we interact EcoPU with CO_2 intensity to closely mirror the baseline specification and add it as an additional control to the baseline specification. Column 1 of Table 7 shows the results when controlling for EcoPU interacted with CO_2 intensity. We observe that the effect of CPU is still highly significant and remains similar in magnitude to the baseline specification. Second, we use the ratio of CPU to EcoPU as an alternative to using CPU (column 2 of Table 7). This captures the effect of climate policy uncertainty above economic policy uncertainty. We still observe highly statistically significant effects of the ratio (CPU/EcoPU) on investment (the magnitude decreases as a consequence of the new definition, changing the interpretation of the coefficient). Third, we adopt a two-stage approach to control for the effect of EcoPU. In a first stage regression, we estimate a model of CPU controlling for EcoPU as well as country- and year fixed effects. The residual from this model is then included in the second stage model interacted with CO_2 intensity (Column 3 of Table 7). The coefficient of this interacted residual remains negative and highly significant (the

change in the magnitude in a simple reflection of the distribution of the residuals compared to that of CPU). Overall, these results confirm that climate policy uncertainty significantly reduces investment, after controlling for general economic policy uncertainty.

Table 7. Controlling for EcoPU

	(1)	(2)	(3)
	Controlling for EcoPU	Ratio CPU/EcoPU	Residuals
Dep. Var.	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)
Log(CPU)$_t$ X Log(CO2 int)	-0.0344***		
	(0.0111)		
Log(CPU)$_{t-1}$ X Log(CO2 int)	-0.0192*		
	(0.0102)		
Δ Log (Ecopu)$_t$ X Log(CO2 int.)	0.00932		
	(0.0108)		
Δ Log (Ecopu)$_{t-1}$ X Log(CO2 int.)	0.00944		
	(0.0113)		
Δ Ratio(CPU/EcoPU)$_t$ X Log(CO2 int)		-0.0154**	
		(0.00644)	
Δ Ratio(CPU/EcoPU)$_{t-1}$ X Log(CO2 int)		-0.0125	
		(0.00793)	
Δ Residual$_t$ X Log(CO2 int.)			-0.000238**
			(0.000103)
Δ Residual$_{t-1}$ X Log(CO2 int.)			-0.000169
			(0.000103)
Log(EPS)$_t$ X log(CO2 int)	0.0317	0.0327	0.0307
	(0.0306)	(0.0292)	(0.0293)
Log(EPS)$_{t-1}$ X log(CO2 int)	0.00578	0.00729	-0.00134
	(0.0255)	(0.0242)	(0.0232)
N	2044950	2044950	2044950
Country-year FE	Yes	Yes	Yes

Note: Column (1) shows effects when controlling for the Economic Policy Uncertainty from Baker, Bloom and Davis (2016[12]). Column (2) controls for the ratio of CPU/EcoPU. Column (3) controls for a residual that was computed in a first stage regression of CPU on EcoPU with country- and year fixed effects.
Source: Authors.

4.3.3. Heterogeneity

95. Firms of different size may be affected differently by changes in climate policy uncertainty. For example, smaller firms may have different margins of adjustment to policy shocks than larger, financially unconstrained firms. To shed more light on this issue, Table 8 shows the effect of CPU for different firm size groups, following the definition of the European Union: small companies (<50), medium (51 – 250) and large (>250) companies. Since companies are grouped according to size, regressions coefficients are not weighted (the unweighted regression on the full sample returns a coefficient of -.0119***, consistent with the sample being dominated by small firms).

96. Table 8 shows that the effect found in the baseline regressions is mostly driven by large firms. For large firms with 250 employees and above, the elasticity is 2.7%, close to the results presented in Table 4. However, for small firms, the elasticity is much smaller at 1.0%. We conclude from this analysis that large firms respond disproportionately to climate policy uncertainty shocks and are responsible for most of the drop in investment uncovered in this study.

Table 8. Firm-size heterogeneity

	(1)	(2)	(3)
	Small Enterprises	Medium Enterprises	Large Enterprises
Dep. Var.	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)
Δ log(CPU)$_t$ X log(CO_2 int)	-0.0106*	-0.0101	-0.0273***
	(0.00629)	(0.00687)	(0.0102)
Δ log(CPU)$_{t-1}$ X log(CO_2 int)	-0.00700	-0.00596	-0.00769
	(0.00518)	(0.00681)	(0.00984)
Δ log(EPS)$_t$ X log(CO_2 int)	-0.0389*	0.00241	0.0754**
	(0.0199)	(0.0205)	(0.0299)
Δ log(EPS)$_{t-1}$ X log(CO_2 int)	-0.0777***	-0.00332	-0.0342
	(0.0184)	(0.0193)	(0.0251)
N	1894303	314249	99081
Country-year dummies	yes	yes	yes

Note: The European classification of Small and Medium-sized Enterprises (SMEs) is used. Small Enterprises: 0-49 employees, Medium Enterprises: 50 – 249 employees, Large Enterprises: 250 employees and above. All columns estimated by OLS. Standard errors clustered at country-sector level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

97. Similarly, firms with different capital intensity or capital-to-labour ratio may be affected heterogeneously by changes in climate policy uncertainty. Fixed assets are typically more irreversible than other types of capital, so that firms with a high capital intensity (defined as fixed assets per unit of output) may react more strongly to increases in CPU than low capital intensity firms. To analyse this issue, we divide firms into groups using the median capital intensity as a cut-off. We define capital intensity as average fixed assets divided by average turnover over the sample period. Similarly, we divide firms into groups with an above- and a below median capital-to-labour ratio.[10]

98. Table 9 shows that the relationship between climate policy uncertainty and investment are driven by capital intensive firms with coefficients larger and more significant in columns (2) and (4), corresponding to above-median capital intensity and capital-labour ratio. Interestingly, we also observe that the coefficients of CPU are larger and more significant at t-1 for the most capital intensive firms, relatively to the baseline specification. Capital intensive investments tend to have a longer lead time and require longer term planning, which may explain the stronger effect at time t-1. Overall, this supports the theoretical prediction that policy uncertainty is particularly harmful for firms that have a higher share of irreversible investments in fixed assets (Bernanke, 1983[6]; Dixit and Pindyck, 1994[9]; Pindyck, 1988[8]). Due to longer lead times of capital intensive investments the effects of climate policy uncertainty may also be more persistent over time.

99. Additionally, we examine if climate policy uncertainty has heterogeneous effects according to labour productivity. Firms at the frontier of the productivity distribution may be more likely to invest in cutting-edge technologies that can be risky and require a certain policy environment to be successfully placed in the market. Managers of the most productive firms may also be more alert to changes in climate policy and therefore adjust investments more strongly. To shed more light on possible heterogeneous effects, we divide

[10] The capital-to-labour ratio measures the relative importance of fixed capital relative to labour for a firm. We measure the capital-to-labour ratio as the average fixed assets divided by the average number of employees.

firms into three groups based on their level of productivity (output per worker)[11]: firms with below-median productivity; firms with a productivity between 50 and 90% of the productivity distribution; and firms in the top 10% of the productivity distribution. Results are shown in Table 10. We observe that effects are strongest for firms at the frontier of the productivity distribution (Column 3). A 10% increase in CPU for the average exposed firm decreases investment by close to 7% in year *t* among the most productive firms. The magnitude of the effect increases two-fold relative to the average effects across all firms in the baseline specification.

Table 9. Heterogeneous effects by capital intensity and KL-Ratio

	(1)	(2)	(3)	(4)
	<50 Cap. Int.	>50 Cap. Int.	<50 K-L Ratio	>50 K-L Ratio
Dep. Var.	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)
log(CPU)$_t$ X log(CO2 int)	0.000861	-0.0382***	-0.0151**	-0.0369***
	(0.0103)	(0.0120)	(0.00751)	(0.0117)
log(CPU)$_{t-1}$ X log(CO2 int)	-0.000175	-0.0223**	-0.0155**	-0.0229**
	(0.0117)	(0.0107)	(0.00714)	(0.0103)
log(EPS)$_t$ X log(CO2 int)	-0.00619	0.00549	-0.0178	0.0101
	(0.0228)	(0.0360)	(0.0236)	(0.0340)
log(EPS)$_{t-1}$ X log(CO2 int)	-0.00389	-0.0155	-0.0648***	-0.0138
	(0.0248)	(0.0320)	(0.0198)	(0.0305)
N	1150098	1150104	1153027	1153040
Country-year FE	Yes	Yes	Yes	Yes

Note: Column (1) shows effects for firms with below-median capital intensity defined as average capital divided by average turnover. Column (2) shows effects for firms with above median capital intensity. Column (3) shows results for firms with a below-median K-L Ratio defined as average capital divided by the average number of employees. Column (4) shows results for firms with an above median K-L Ratio.
Source: Authors.

Table 10. Heterogeneous effects by firm productivity

	(1)	(2)	(3)
	<50 Productivity	50-90 Productivity	>90 Productivity
Dep. Var.	Δ log(I_t)	Δ log(I_t)	Δ log(I_t)
log(CPU)$_t$ X log(CO2 int)	-0.0141	-0.00998	-0.0684***
	(0.0133)	(0.00977)	(0.0210)
log(CPU)$_{t-1}$ X log(CO2 int)	-0.000556	-0.0136	-0.0229
	(0.00977)	(0.00840)	(0.0204)
log(EPS)$_t$ X log(CO2 int)	-0.0128	-0.00612	0.0472
	(0.0329)	(0.0251)	(0.0609)
log(EPS)$_{t-1}$ X log(CO2 int)	-0.0263	-0.0239	-0.0410
	(0.0342)	(0.0285)	(0.0478)

[11] We define productivity as output per worker measured as average turnover divided by average employees.

N	1149417	919530	229892
Country-year FE	Yes	Yes	Yes

Note: Productivity is measured as output per worker (average turnover / average employees). Column (1) shows results for firms with a below-median productivity. Column (2) shows results for firms with a productivity between 50 and 90% of the productivity distribution. Column (3) shows results for the 10% most productive firms. Standard errors clustered at country-sector level in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.
Source: Authors.

5. Conclusion

100. This study proposes a new indicator of Climate Policy Uncertainty based on newspaper coverage frequency. The indicator covers 12 OECD Member Countries and covers the period 1990-2018. The index spikes near major political events and during major discussions around potentially significant climate policy changes. This study additionally constructs indicators relying on frequency counts at the monthly and quarterly level for a subset of countries. The additional granularity allows to further investigate variations in the index over time in more detail. Finally, it also provides two additional sub-indices to systematically disentangle the direction of the uncertainty and inspect whether an increase in the index is associated with a weakening or a strengthening of climate policies.

101. As a first application of the index to firm-level data, this paper examines the relationship between climate policy uncertainty and investment. Using a global firm-level dataset, the empirical analysis shows that Climate Policy Uncertainty is associated with statistically and economically significant decreases in investment, particularly in pollution-intensive sectors that are most exposed to climate regulation. We show that a 10% increase in CPU for the average exposed firm decreases investment by 2-3%, with stronger effects for carbon intensive firms.

102. Exploring firm heterogeneity, the study finds that the effects are stronger for large and more capital-intensive firms. The findings generally support the theoretical prediction that policy uncertainty is particularly harmful for firms that have a higher share of irreversible investments. The effects of climate policy uncertainty may also be more persistent over time for more capital-intensive companies. We also show that the effect of climate policy uncertainty is strongest for firms closer to the frontier of the productivity distribution.

103. Overall, the results suggest that the general increase in climate policy uncertainty observed in the countries covered by our indicator in recent years may have significantly slowed down investment efforts by the most carbon-intensive sectors of the economy – those that contribute most to emissions of greenhouse gases and local air pollutants. To the extent that part of these foregone investments would have been dedicated to upgrading production processes toward more low-carbon assets, these results provide the first large-scale micro-level empirical evidence to support the oft-made policy recommendation that policy stability is key for the transition to a low-carbon economy.

104. Nevertheless, it is illusory to hope that all policy uncertainty could be eliminated, as discussions over any new climate policy package – or over potential strengthening of existing regulations – as part of usual democratic processes are bound to generate uncertainty. Policies also need to include some flexibility mechanisms to be able to adapt to new scientific information or changing macroeconomic conditions, so that not all climate policy uncertainty is bad. However, such mechanisms could be embedded in the policy design since the outset, limiting the room for arbitrary adjustments, which may contribute

to the uncertainty and its impact as analyzed in this section (Annicchiarico et al., 2022[59]) . Further, a unique feature of climate policy uncertainty is that in the case of climate policy, the economy needs to transition from a high-carbon to a low-carbon equilibrium. Hence, policy uncertainty can be driven by hints at accelerations in this transition as well as at slowdowns. However, many of the uncertainty spikes observed in the CPU index are associated with unforeseen changes in policies, such as dismantling of existing policy instruments like emissions trading systems and sudden lowering of existing climate change related standards. Such sudden policy reversals can reduce business confidence in existing policies, which may therefore delay or reduce investments. As demonstrated by this paper, limiting avoidable policy uncertainty through forward-looking and well-designed policies could have large positive effects on investment.

105. This index paves the way to new research on climate policy uncertainty in a variety of realms and on a variety of outcomes. Future work could aim at distinguishing between unavoidable and avoidable policy uncertainty, and assess the benefits of eliminating the latter in terms of increased investment. To the extent that such data exists, future work could also complement this study by assessing the effect of climate policy uncertainty on clean and dirty investment separately. Although the scale effect is clear from a theoretical point of view – higher uncertainty unambiguously reduces overall investment – the predicted impact on clean versus dirty investment is less clear-cut, particularly if uncertainty is accompanied by an increase in the predicted future level of environmental policy stringency. This study confirms the theoretical prediction that the net effect on overall investment is negative, but assessing the effect on the direction of investment is a promising research avenue.

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Annex A. Search Strategy

The search strategy was built to maximize the number of relevant articles picked up (minimising the number of "false negatives" not picked up by the search) while minimizing the number of irrelevant articles wrongly selected (avoiding "false positives"). In order to optimize the search strategy, we empirically tested a high number of specifications. After each try, we read in full the first 50 articles associated with each specification and counted the number of false positives. At various stages, we also conducted random checks across multiple years in the entire sample (reading in full 100 randomly selected articles) to ensure that the quality of our search strategy was not biased toward the most recent articles.

Minimising false positives

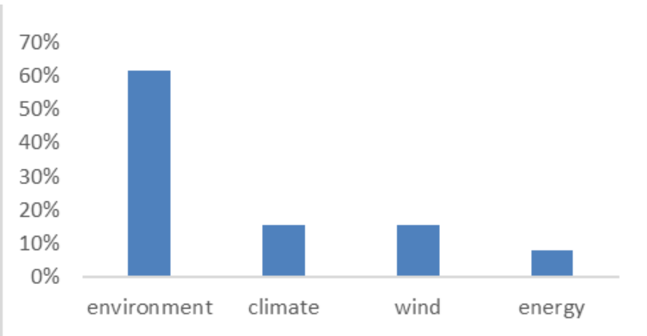
We started with the following baseline search strategy:

(energy or environmental or "climate change" or climate or carbon or emissions or CO_2 or wind or solar or renewable or pollution or pollutant or SOx or NOx or "particulate matter" or "fine particulates" or PM or SO2 or ozone or "electric vehicles" or "hybrid vehicles" or "hydrogen vehicles" or EVs) and (policy or policies or regulation or regulations or legislation or legislations or law or laws or fee or fees or tax or taxes or standard or standards or certificate or certificates or subsidy or subsidies or pricing or ETS or "trading scheme" or "trading system" or "cap and trade" or "emissions trading") and (uncertain or uncertainty)

This baseline strategy was tested using the Wall Street Journal in the US.

A first step was to understand which keywords generated the most false positives. The result of this first step is summarised in Figure A.1.

Figure A.1. Keywords generating false positives



Note: This table shows the proportion of false positives by keyword after reading the first 50 articles selected through the baseline search strategy presented above.
Source: Authors calculations from Factiva.

Environment keywords

A first observation is that all the main keywords generating a high number of false positives are included in the environment bracket. In particular, the word environment accounts for more than half of false positives, most likely because it can also signify overall surrounding conditions and settings. Our search strategy then catches expressions like "regulatory environment", "geopolitical environment", etc. Because "environment" is a broad term, it is impossible to exclude all the expressions associated with environment that bring noise into the search. However, when environment does not refer to nature, we noticed that it was often used in an indefinite form or following an adjective. We thus chose to exclude "environment" from the search but to include "the environment" and the adjective environmental and adverb environmentally, which are more specific. Empirically, this change drastically brought down the number of false positives.

Similarly, the keyword "climate" can also refer to conditions and settings. However, contrary to "environment", "climate" is in most cases associated with nature. Excluding "climate" would leave out large numbers of relevant articles. We thus identified a list of expressions including "climate" to exclude. To do so, we looked at how many articles did include a specific climate-associated expression in the baseline search strategy. We excluded from the search the expressions that came back most often (see Table A.1 for a list of the expressions tested).

Table A.1. Expressions containing the keyword "climate"

"…" climate	Occurrences	Comments
political	52	
business	23	
economic	17	
regulatory	12	
legal	9	
fair	0	
uncertain	5	
competition	0	
competitive	0	
industrial	0	
industry	0	
banking	0	
geopolitical	0	
policy	2	
financial	2	
production	0	
fiscal	0	
market	0	
social	0	
regulatory	12	
this climate	2	
that climate	15	50% are relevant
a climate	64	70% of articles are relevant

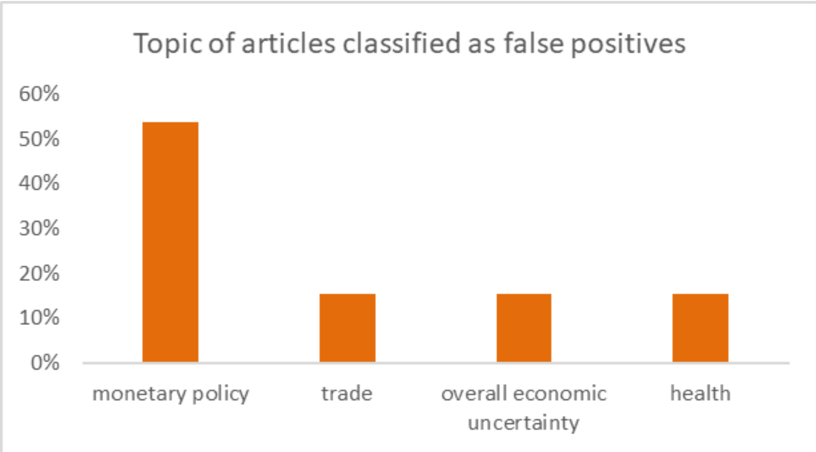
Source: Authors' calculations from Factiva.

False positives associated with the keyword "wind" correspond to using the term as a verb ("wind up") or to particular idioms ("having the wind to its back"). To avoid these, we replaced "wind" with expressions specific to renewable energy such as "wind energy" "wind farm" and "wind turbine".

Policy keywords

We then investigated the false-positive articles picked up through the policy keywords. The result of this analysis can be seen in Figure A.2. The most common topic among false positives is related to monetary policy. We thus decided to exclude "monetary policy" from the set of policy keywords, implying that an article mentioning monetary policy can only be selected if it also includes at least another policy keyword. Even though this may be subject to change in the future, monetary policy is in our time period still largely independent from climate policy. Excluding other topics such as "trade policy" or "economic policy" would have led us to exclude too many relevant articles, so we left these in.

Figure A.2. Proportion of false positives by policy topic



Source: Authors' calculations from Factiva/Nexis.

Uncertainty keywords

Because uncertainty is diffuse and unobserved, it may transpire through articles that do not include the word uncertainty per se but synonyms. We empirically determined which synonyms of uncertainty would be the most relevant to include according to (1) the number of articles added and (2) the number of false positives generated. To test the number of articles added, the uncertainty bracket was replaced by a number of potential synonyms one by one (excluding uncertain and uncertainty). Table A.3 presents the results of these tests for a number of synonyms. Because they add the most articles and bring in the least false positive, we decided to add vague and unclear to the uncertainty bracket. Other synonyms were discarded as the proportion of false positives was deemed to high (>20%). For example, we decided to discard the term "risk" because, although it greatly increases the number of articles caught, those additional articles include a high share of false positives.

Table A.2. Potential uncertainty keywords

Keyword	Article Count	% of False Positives in First 50
unclear	1398	16%
vague	462	14%
risk	6852	32%
unsure	144	32%
undecided	223	48%
ambiguous	160	22%
unstable	206	24%
unpredictable	346	34%

Source: Authors’ calculations from Factiva/Nexis.

Distance between keywords

The distance between the terms of the different brackets of the search strategy within an article is another important parameter. It is likely that, for an article to refer to environmental policy, the environment and the policy terms need to be located close to each other. Indeed, chances are high that, if an article mentions an environmental topic in the first paragraph and a policy term in the last, both are unrelated and thus not of interest to this project. Table A.3 presents the results of some of the different specifications tested. The baseline strategy is to impose that the environment and policy keywords have to be included in the same paragraph, while the uncertainty keyword can be located anywhere in the article (specification 1). Imposing that all three keywords (including uncertainty) are located in the same paragraph drastically reduces the number of articles picked up while inflating the rate of false positives (specification 2). An intermediate option – more restrictive than specification 1 but less than specification 2 – would be to impose that the policy and environment terms are in the same sentence, considering that the average English sentence is 16-18 words (specifications 3-5). However, this cut-off is quite arbitrary and, in addition, catches 20% less articles than the specification where the environment and policy keywords have to be within the same paragraph. Therefore, our preferred specification is to impose that the environment and policy keywords fall within the same paragraph but not to impose any distance with the uncertainty keyword (specification 1).

Table A.3. Search results for various proximity conditions

Strategy	Article Count	% False Positives in First 50
Baseline: (environment) same (policy) and (uncertainty) **(1)**	5448	6%
(environment) same (policy) same (uncertainty) **(2)**	1235	14%
(environment) near 16 (policy) and (uncertainty) **(3)**	4155	2%
(environment) near 17 (policy) and (uncertainty) **(4)**	4256	2%
(environment) near 18 (policy) and (uncertainty) **(5)**	4349	2%

Final Search Strategy for English-speaking countries

After these adjustments, we obtain the final 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 CO_2 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)

Rate of false positives

We checked the validity of the search strategy using the Wall Street Journal. First, we reported the share of false positives in the first 50 articles, as for the other specifications, and additionally read more than 100 articles at random from the entire sample. With the current search strategy, the number of relevant articles is above 90%. Table A.4 presents the share of false positives for the final search strategy using those two methods.

More importantly, with this search strategy, the remaining false positives seem to be random. If we consider the three remaining false positives among the first 50 articles picked up by our search strategy for the Wall Street Journal, the first one refers to the volatility of the climate, but to uncertainty from trade and not from environmental policy. The second false positive is an article on health policy that cites energy markets as a counter-example, using the phrase (“Unlike energy markets”). The last false positive stems from a misuse of the term “energy”, referring to the “time and energy” of President Trump.

The number of false positives is relatively low and the remaining false positives are difficult to exclude without losing many relevant articles. For example, the term “energy” could be excluded because it generates false positives associated with articles mentioning the energy of individuals, but this would entail losing many relevant articles concerning energy policy. We thus consider that this search strategy is preferred given the existing trade-off between maximising the number of relevant articles and minimising the number of false positives.

Table A.4. Rate of false positives in final search strategy

Specification	Article Count	Methodology	% False Positives
Final search	5448	Read Through First 50 articles	6.0%
Final search	5448	Random Check of 102/5448	9.8%

Final Search Strategy for the alternative versions of the index

This section reports the search strategies used to compute the alternative climate policy uncertainty indicators introduced in Section 3.3. By taking advantage of the differences in topical scope between the original and the alternative versions of the indicator, we can further explore the underlying drivers of uncertainty and investigate the following. First, N-CPU examines whether variations in our baseline index are fundamentally driven by uncertainty about policy developments targeting other environmental concerns than climate regulation, which could have been captured by the original search strategy. Second, our sub-indices – CPU+ (“CPU plus”) and CPU- (“CPU minus”) - are used to assess whether an increase in our index suggests that the low-carbon transition is slowing or accelerating.

Search Strategy with additional keywords related to the strengthening of climate policy (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") not (loosen* or weaken* or relax* or dismantl* or dilut* or lower or decreas* or deteriorat* or rollback or "roll back" or "rolling back" or ease)) near500 (strength* or tighten* or reinforc* or stronger or firmer or "more stringent" or "more rigid" or tough* or stiff* or strict*) and (unclear or vague or uncertain or uncertainty)

Search Strategy with additional keywords related to weakening or failure of climate policy (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 (loosen* or weaken* or relax* or dismantl* or dilut* or lower or decreas* or deteriorat* or rollback or "roll back" or "rolling back" or ease) 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)

Final Search Strategy for non-English-speaking countries

The search strategy was translated and empirically adapted for each country. Translations are not only literal because some words may be associated with double meanings in some languages. For example, in the French search strategy, the word “environment” was excluded from the search altogether because it generated too many false positives (beyond

30%) due to its use as a synonym for conditions and settings. Contrary to English, adding an article ("l'environnement") could not solve the issue.

Specific country-level energy legislations were also added when relevant. For example, the German renewable energy legislation package "EEG" or "Erneuerbare Energien Gesetz" was included in the German search.

Search Strategy for 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 CO_2* 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)

Search Strategy for 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 CO_2 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"")

Search Strategy for 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 CO_2 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")

Search Strategy for 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 CO_2 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)

Rate of false positives for non-English speaking countries

We checked the validity of the search strategy in each country based on the main newspaper. The results of this analysis is presented in Table A.5. The proportion of false positives is below 10% for the vast majority of newspapers and only slightly above for Les Echos.

Table A.5. False positives rate for selected newspaper

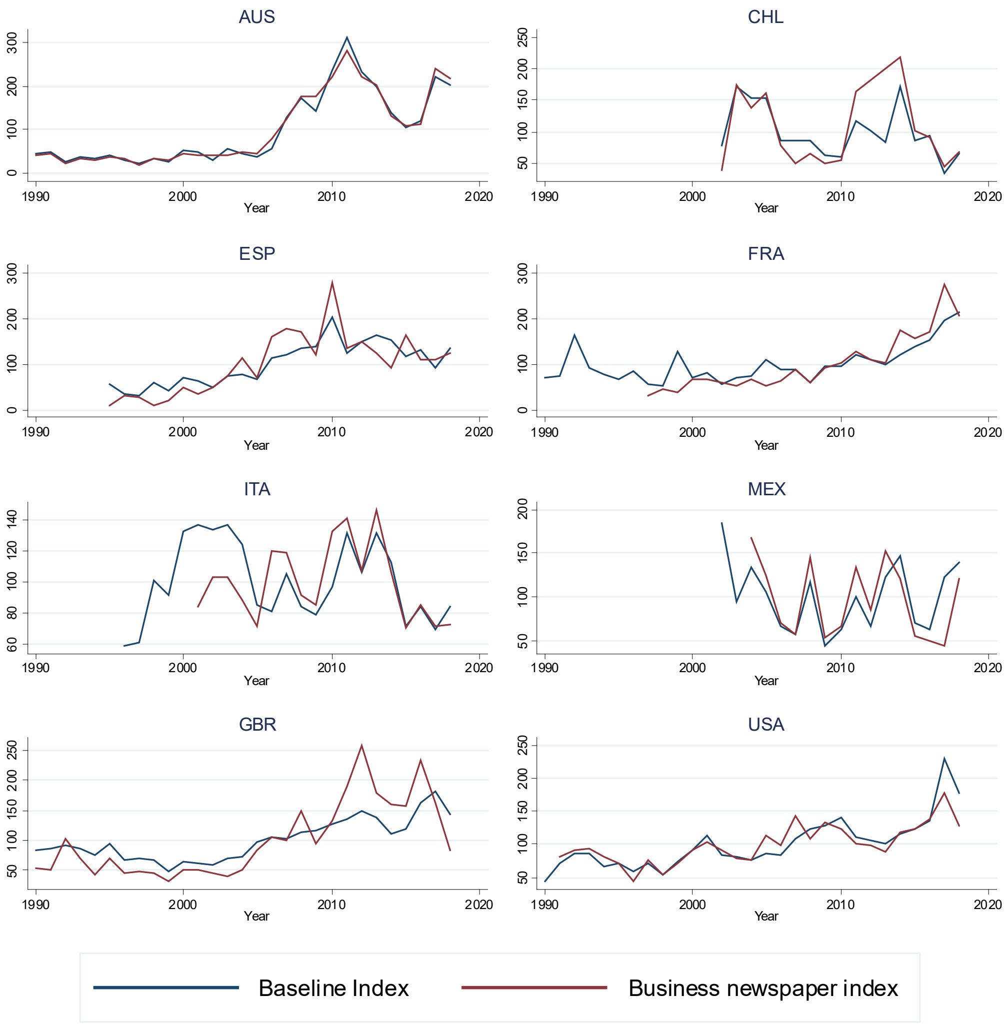
	Article Count	% of False Positives in First 50
Wall Street Journal (US)	5448	6%
Financial Times (UK)	1782	6%

Globe and Mail (CA)	1614	8%
Les Echos (FR)	472	12%
Australian Financial Review (AU)	3657	0%
Süddeutsche Zeitung (DE)	1546	10%
Il Sole 24 Ore (IT)	1806	4%
Expansion (ES)	921	8%

Source: Authors calculations using Factiva/Nexis.

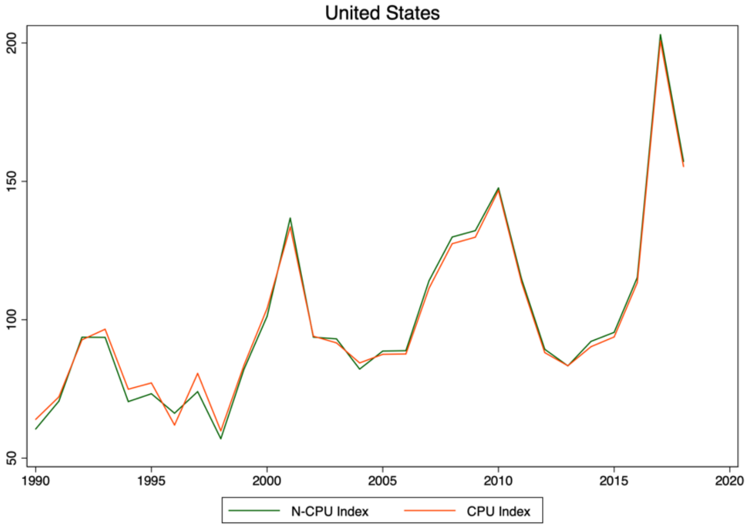
Annex B. Alternative Indices

Figure A B.1. Baseline Specification and Business Newspaper



Note: For each of the countries above, the baseline measure is compared to a measure using only the largest business newspaper. Because we were unable to obtain data for the largest business newspapers in Germany, Ireland, New Zealand, and Canada, these countries are not represented here. In addition, the index computed using a single newspaper is still standardized to mean 100 in order to be able to compare it to the countrywide index. List of newspapers selected as "business newspapers": Australia *The Australian Financial Review,* Chile *Il Diario Financiero,* France, *Les Echos*, Italy *Il Sole 24 Ore*, Mexico, *Il Financiero*, Spain, *Expansion*, the UK, *The Financial Times,* The United States, *The Wall Street Journal*.

Figure A B.2. Narrow version of CPU (N-CPU)

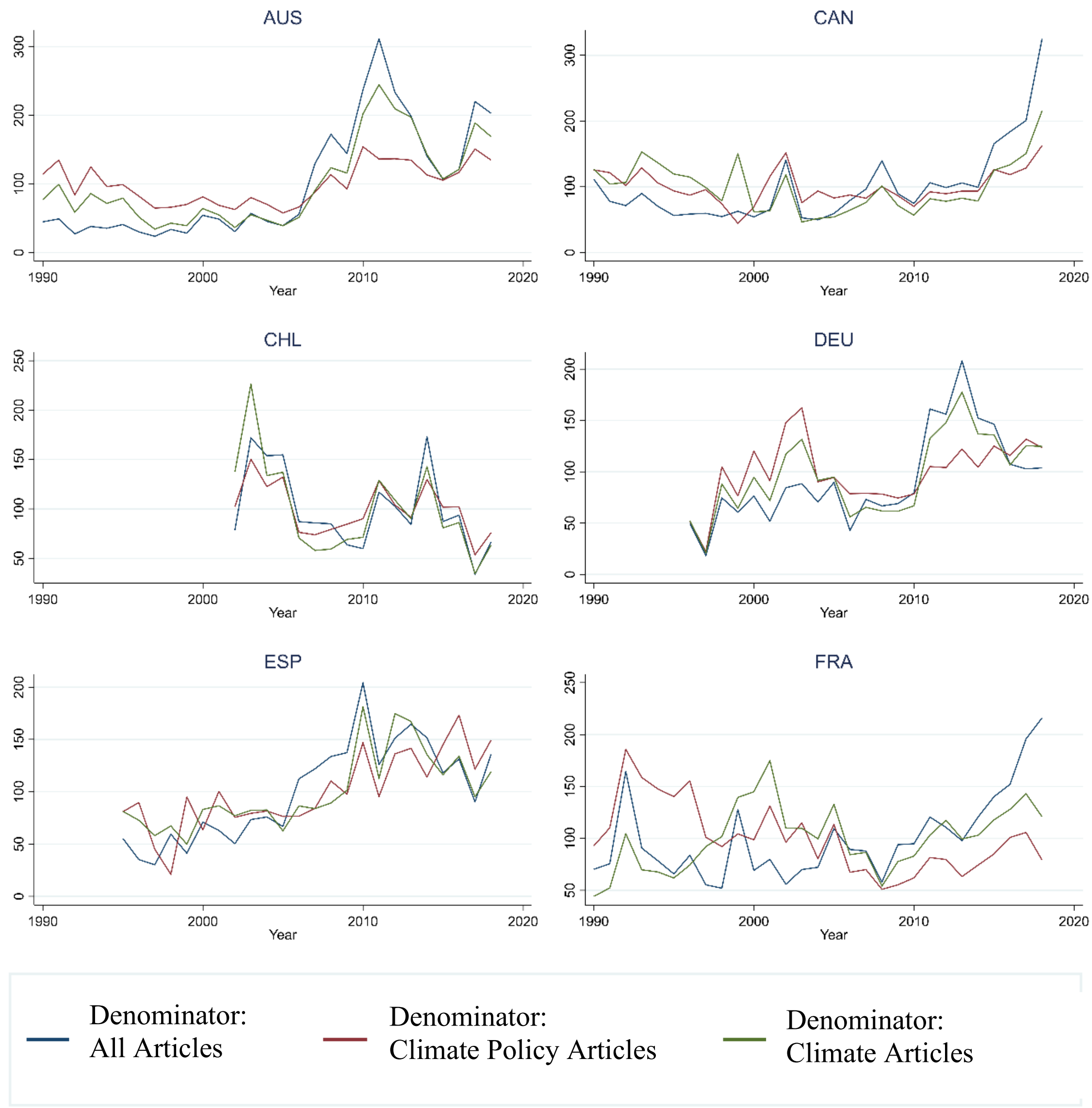


Note: The Figure shows the narrow version of the CPU index, based on the narrower search strategy that excludes terms relating to air pollution.
Source: Authors' calculations based on Factiva data.

Annex C. Alternative Indices – Denominators

Figure C.1. Variations in the denominator of the Indicator– Part 1

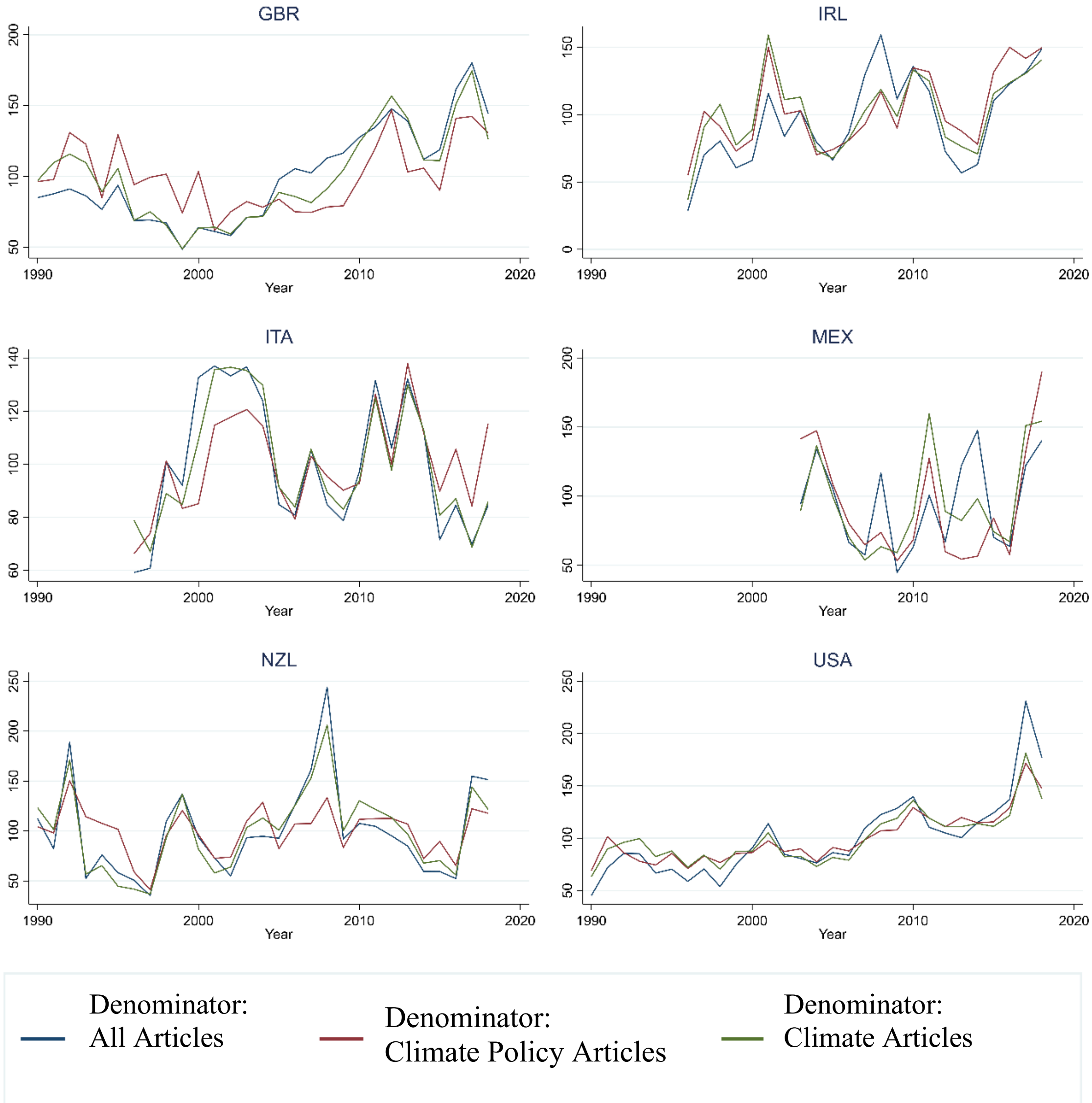
Baseline, Environment Articles Specification, Environment Policy Articles Specification



Note: On each country graph, the blue line corresponds to the baseline specification which uses total newspaper article count as the denominator of the index. The red line corresponds to the specification where the denominator is replaced by the number of articles talking precisely about climate policy. Finally the green line represents the specification where the denominator of the index is replaced by the number of articles talking about the environment and the climate.

Figure C.2. Variations in the denominator of the Indicator– Part 2

Baseline, Environment Articles Specification, Environment Policy Articles Specification

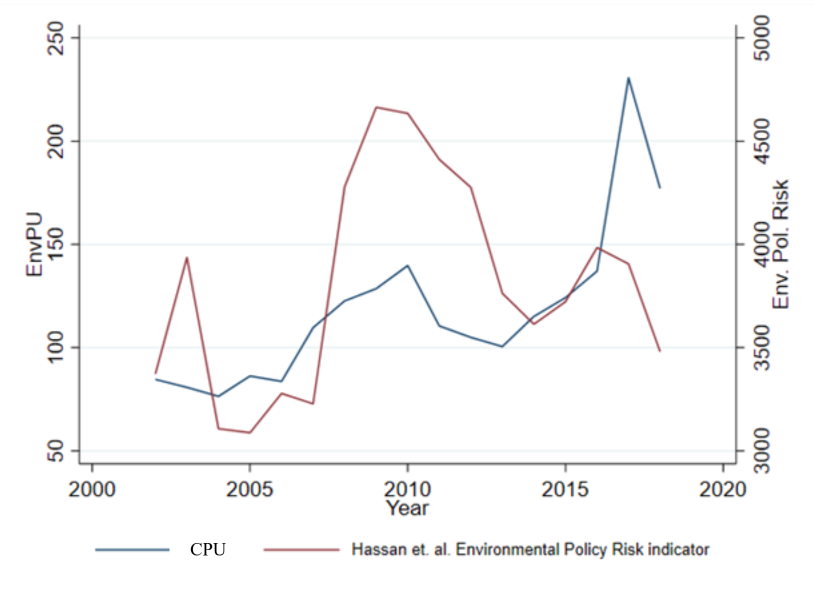


Note: On each country graph, the blue line corresponds to the baseline specification which uses total newspaper article count as the denominator of the index. The red line corresponds to the specification where the denominator is replaced by the number of articles talking precisely about climate policy. Finally the green line represents the specification where the denominator of the index is replaced by the number of articles talking about the environment and the climate.

Annex D. US CPU and Environmental Policy Risk Indicator from Hassan et al. (2019)

Figure D.1. plots the unweighted average of the firm-specific environmental risk indicator against the CPU index for the U.S. We observe that the two indices follow each other quite closely for most of the time series, in particular during the period 2004-2014, but also note that the indices differ in the earlier or later years. It is important to note that the firm-level indicator developed by Hassan et al., (2019[47]) captures risk from environmental policies as reported by listed firms. Such risks to firms may be different from overall uncertainty from environmental policies to the economy as reported by major newspapers. In particular, a stringent but certain policy might carry high risk for firms (for example if they can expect for sure to be faced with a high pollution tax). This would show as a peak in the political risk indicator but not in the CPU indicator. Overall, however, the similar trends in the indices strengthens our confidence in the CPU Index.

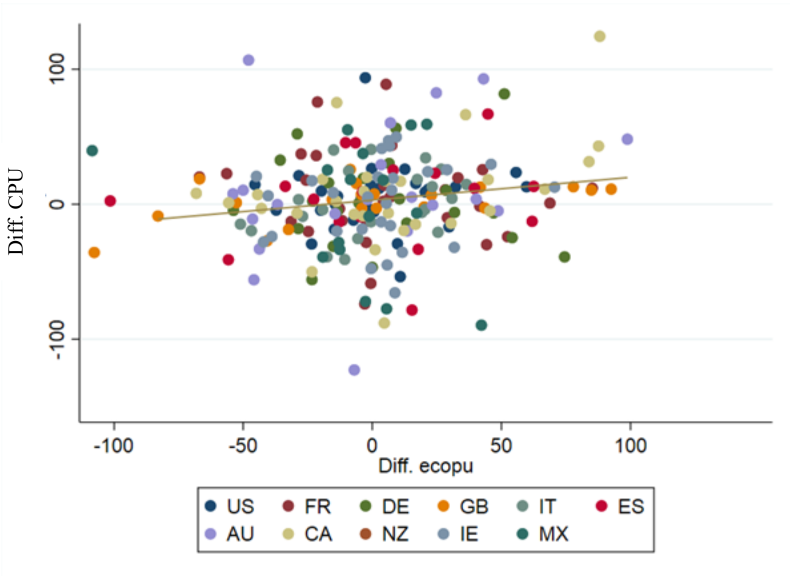
Figure A D.1. US CPU and Environmental Policy Risk Indicator from Hassan et al. (2019)



Source: US CPU indicator as above. The average environmental policy risk indicator is computed as an unweighted average using the data provided by Hassan et al. (2019[47]).

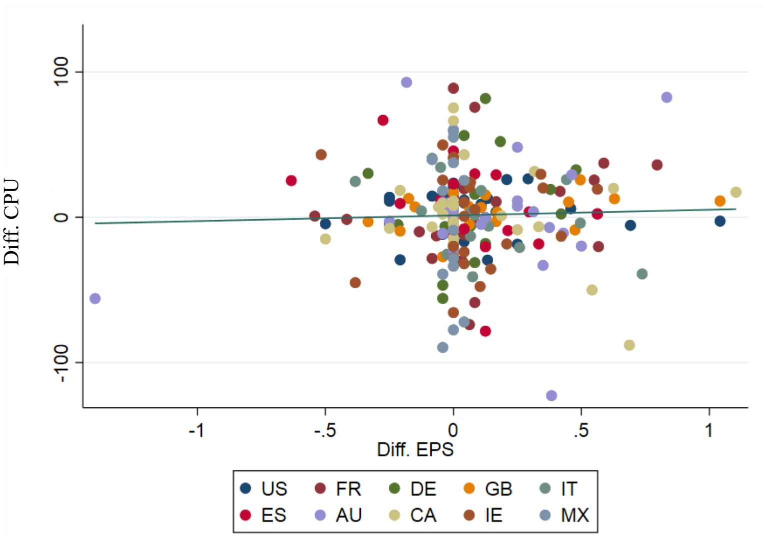
Annex E. Within-country correlations of CPU, EcoPU and EPS

Figure A E.1. Within-country correlation between CPU and EcoPU



Note: The graph shows the within-country year-on-year differences in CPU versus the within-country year-on-year differences in EcoPU. The correlation coefficient is 0.16.
Source: CPU as above. The Economic Policy Uncertainty data is obtained from Baker, Bloom and Davis (2016[12]).

Figure A E.2. Within-country correlation between CPU and EPS



Note: The graph shows the correlation between the within-country year-on-year differences in CPU versus the within-country year-on-year differences in EPS. The correlation coefficient is 0.04.
Source: CPU as above. EPS: (OECD, 2019[54]).

Annex F. Economic Policy Uncertainty and CPU

Figure F.1. Climate Policy Uncertainty and Economic Policy Uncertainty (EcoPU) Part 1

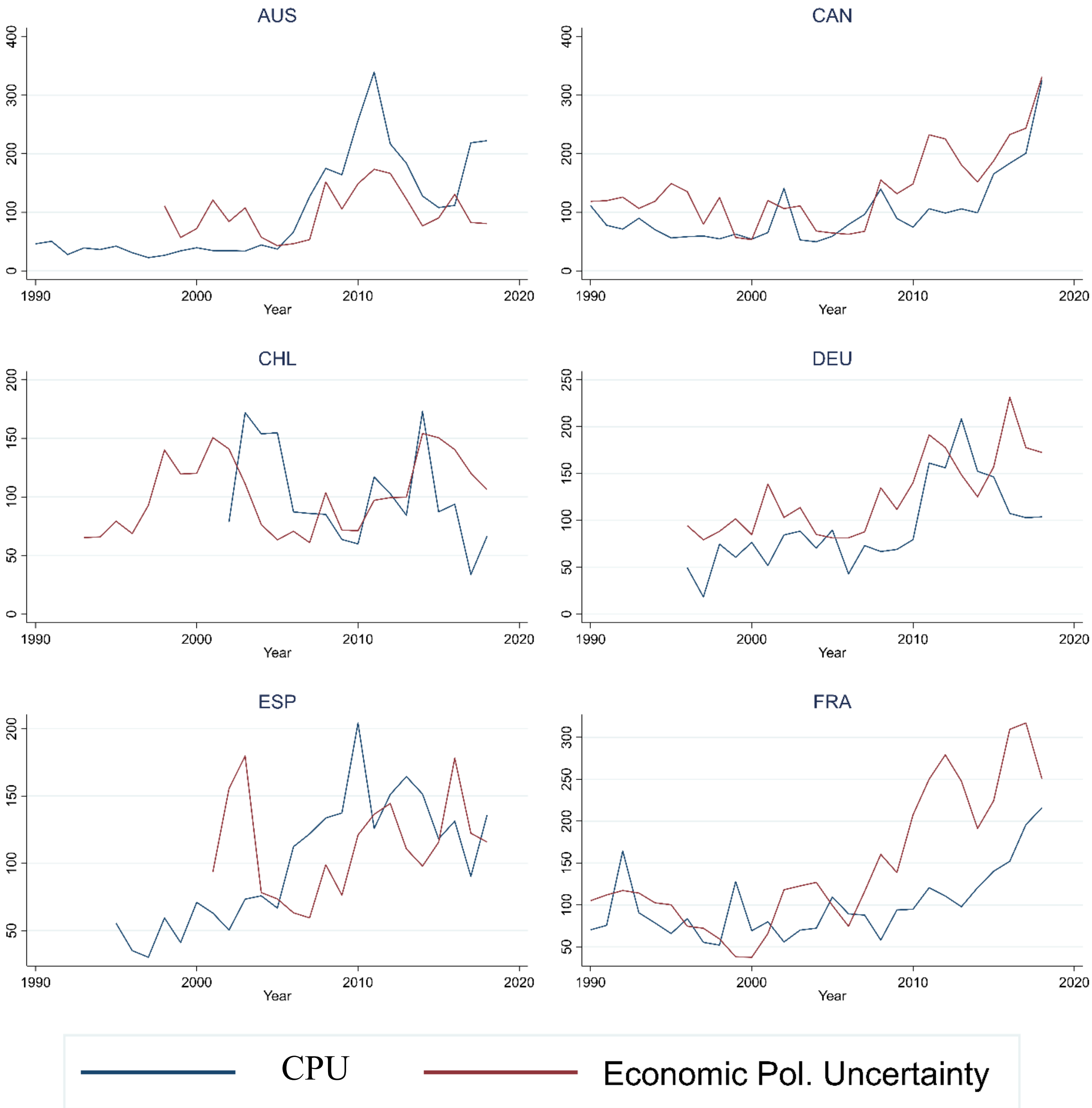


Figure F.2. CPU and Economic Policy Uncertainty (EcoPU) Part 2

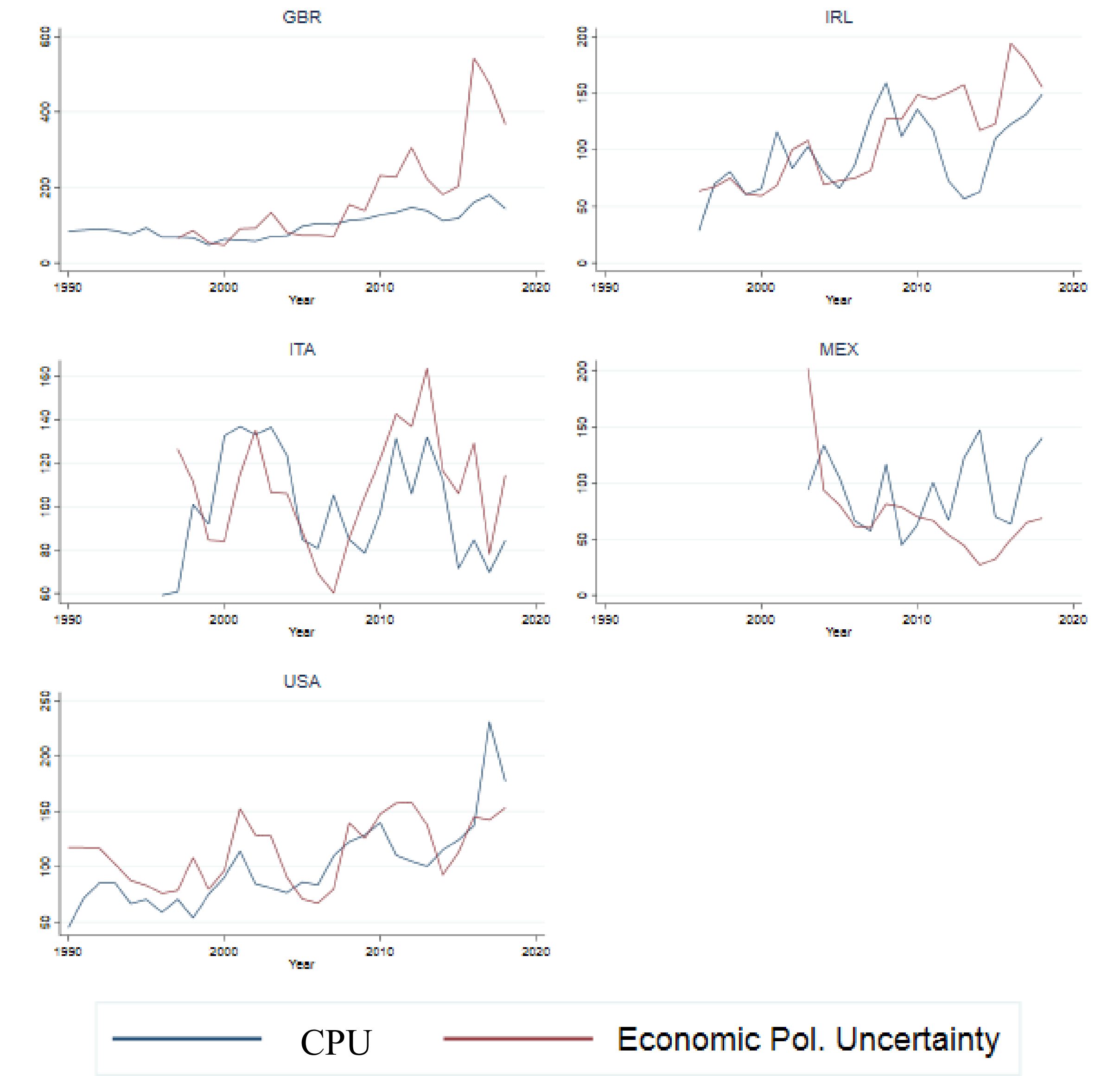
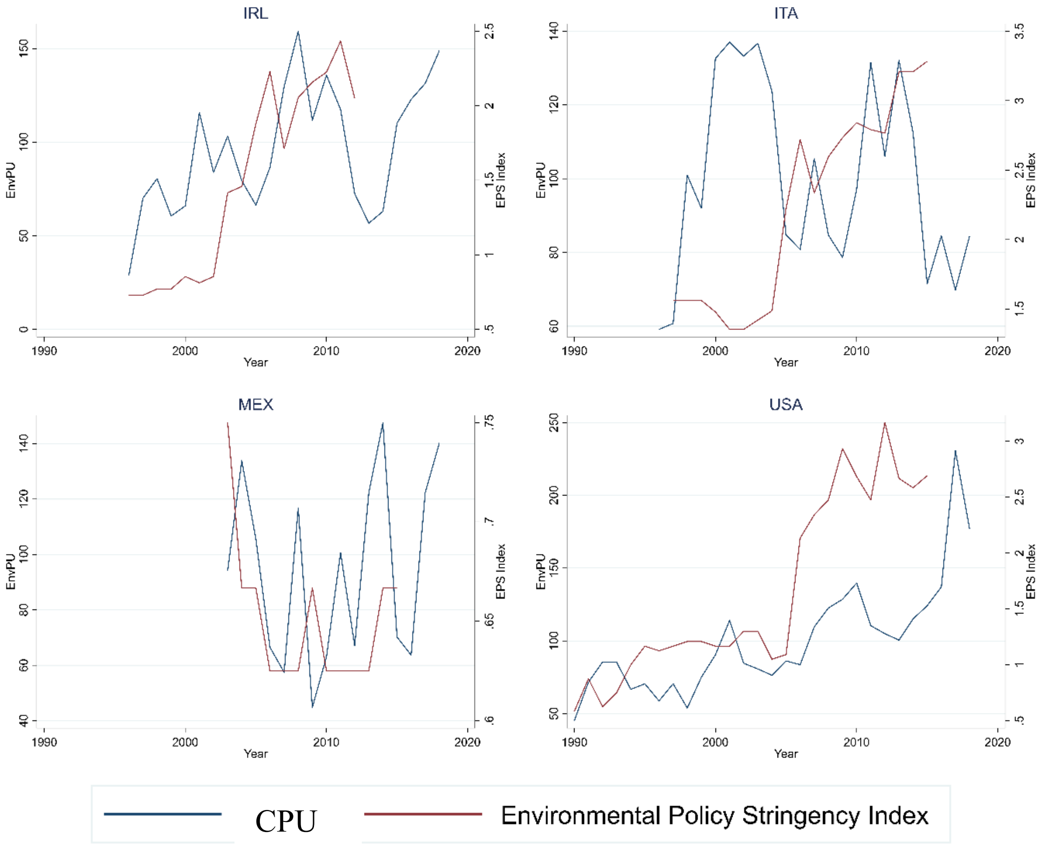


Figure G.2. CPU and EPS (Part 2)



Note: The blue line shows the climate policy uncertainty indicator. The red line shows the Environmental Policy Stringency Index (OECD, 2019[54]). The OECD EPS indicator is not available for Chile.
Source: For the EPS, see Botta and Koźluk (2014) and OECD (2017[1]).

Annex H. Descriptive Statistics

Table A H.1. Descriptive Statistic

	Observations	Mean	Standard Deviation	Min	Median	Max
Log(I)	2,283,131	10.60	2.58	-0.41	10.64	23.93
Log(I/K)	2,276,996	-1.96	1.84	-18.63	-1.77	9.46
Log(CPU)	2,283,131	4.56	0.35	2.91	4.61	5.83
Log(EPS)	2,283,131	0.89	0.32	-0.21	1.01	1.40
Log(Average CO_2 intensity)	2,283,131	4.35	1.13	2.04	4.00	8.89

Note: The above table presents descriptive statistics for firms in the working dataset constructed from the OECD Orbis database. To be included, firms must have investment information available in Orbis for at least 5 years and belong to sectors with a NACE code up to 43.
Source: Orbis database.