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THE MACROECONOMIC EFFECTS OF CLIMATE POLICY UNCERTAINTY

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ABSTRACT

We develop a measure of climate policy uncertainty based on newspaper coverage. Our index spikes during key U.S. climate policy events—including presidential announcements on international agreements, congressional debates, and regulatory disputes—and shows a recent upward trend. Using a novel instrument for plausibly exogenous uncertainty shifts, we find that higher climate policy uncertainty decreases output and emissions while raising commodity and consumer prices, acting as supply rather than demand shocks. Faced with this trade-off, monetary policy does not accommodate climate policy uncertainty shocks, shaping their transmission. Firm-level analyses show stronger declines in investment and R&D when firms have higher climate change exposure.

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1. Introduction

Climate change has wide-ranging environmental, economic, and social implications. In response, governments around the world have begun to implement policies to confront climate change. However, the future direction of climate policy remains highly uncertain. Nowhere is this more evident than in the United States, where climate policy has been characterized by increasingly large swings: from the failed attempt to introduce economy-wide carbon pricing during the first Obama administration, to a regulatory approach in Obama's second term, to broad deregulation under the first Trump presidency, to the tax and subsidy-based strategy embodied in the Inflation Reduction Act under Biden, and most recently to a pro-fossil-fuel legislative and regulatory agenda under the second Trump administration.

While much of the policy debate has focused on the macroeconomic costs of the climate transition itself, uncertainty about the future course of climate policy may also weigh on economic activity. Yet despite its salience, there is little empirical evidence on how climate policy uncertainty affects the macroeconomy.

This paper provides a comprehensive assessment of the macroeconomic effects of climate policy uncertainty on the U.S. economy. We define climate policy uncertainty as the lack of clarity and predictability surrounding government actions to address climate change. Uncertainty about climate policy can arise from various sources, including political debate around proposed policy changes, uncertainty about implemented policies due to political or legal challenges, or regulatory ambiguity stemming from the complexity of climate policy design. Measuring climate policy uncertainty is challenging, however. We construct a novel index of climate policy uncertainty from newspaper coverage, combining dictionary-based methods with large language model–based classification, and validate it through a comprehensive series of checks, including human audits. Our index spikes during pivotal moments in U.S. climate policy history and captures a distinct source of uncertainty, largely uncorrelated with broader policy uncertainty and other risk indicators. Climate policy uncertainty has surged in recent years, driven to record levels by frequent changes in administrations and their sharply contrasting climate policy approaches.

Estimating the macroeconomic effects of climate policy uncertainty raises three key identification challenges. First, movements in climate policy uncertainty may not be exogenous, as policymakers adjust their climate stance in response to economic developments. Second, climate policy uncertainty may be confounded with broader economic or political uncertainty; for example, U.S. legislation repealing many of the energy tax provisions of the Inflation Reduction Act in 2025 also extended tax provisions unrelated to climate policy. Third, changes in uncertainty are often intertwined with changes in expected policy stringency, making it difficult to disentangle second-moment shocks from first-moment policy news.

To address these challenges, we construct a new narrative-based instrument for climate policy uncertainty. We compile a comprehensive account of U.S. climate policy history and identify 146 major policy events that caused substantial shifts in climate policy uncertainty while being driven primarily by climate-related, political, or ideological considerations. These include shifts in U.S. participation in international agreements such as the Paris Accord, contentious legislative episodes such as the failure of cap-and-trade proposals, and regulatory reversals over states' authority to set stricter emissions standards. We quantify the impact of each event using high-frequency newspaper coverage and isolate the unanticipated component of media reporting. Crucially, our narrative classification identifies events corresponding to both increases and decreases in policy stringency. We then purge the event-level reporting of changes in stringency, isolating variation that reflects shifts in uncertainty rather than policy news.

Using the event-based climate policy uncertainty series as an instrument in a vector autoregression (VAR) model, we estimate the dynamic causal effects of a climate policy uncertainty shock. We find that an increase in climate policy uncertainty leads to a significant fall in industrial production and GDP, higher unemployment, and a fall in investment. At the same time, commodity and consumer prices increase significantly. In terms of magnitude, an increase in climate policy uncertainty by 50 percent, which corresponds roughly to the increase in climate policy uncertainty over the 2016–2020 election cycle, leads to a decrease in output by 0.5 percent, a fall in private investment by close to 2 percent and an increase in the unemployment rate by 0.2 percentage points. Commodity prices increase by around 2.9 percent and headline consumer prices rise by 0.2 percent. The opposing price and quantity responses suggest that climate policy uncertainty shocks transmit to the economy as supply shocks. We show that this sharply contrasts with other policy uncertainty shocks, which tend to propagate like aggregate demand shocks.

This finding has important consequences for the conduct of monetary policy. Following climate policy uncertainty shocks, the policy rate does not change significantly. This is consistent with the fact that the fall in activity coupled with rising inflation creates a trade-off for the monetary authority. The situation is very different for economic policy uncertainty shocks, where the central bank eases the policy rate significantly in response to the fall in output and prices. This in turn helps stabilize the economy and prevent even larger adverse impacts of economic policy uncertainty. Indeed, we show based on counterfactual analyses that monetary policy plays a meaningful role for the transmission of climate policy uncertainty shocks. If the central bank were to accommodate the shock, in line with its response to economic policy uncertainty, the output response is largely stabilized, albeit at the cost of somewhat higher inflation.

We do not find evidence for the 'green paradox' at the aggregate level—the idea that the threat of future climate regulation prompts higher near-term emissions. Instead, we observe that emissions do not change significantly initially but then decline following the fall in economic activity, leaving the emissions intensity largely unchanged. Thus, while uncertainty about future climate regulations leads to emission reductions, this comes at a considerable economic cost.

While the shock leads to a substantial fall in private investment, public investment remains largely unchanged, consistent with our interpretation of a shock operating through uncertainty rather than policy news. Moreover, controlling for an aggregate climate policy news or climate policy sentiment index leaves our results virtually unchanged.

Controlling for broader economic policy uncertainty also has little effect on the estimates. Moreover, climate policy uncertainty shocks do not significantly affect other measures of uncertainty, including broader economic and trade policy uncertainty, geopolitical risk, or financial uncertainty. Together, these findings support the notion that climate policy uncertainty captures a distinct, climate-specific source of uncertainty rather than broader movements in overall policy uncertainty or financial risk.

In line with our notion that climate policy uncertainty shocks transmit as supply shocks, we find a limited impact on consumer sentiment. By contrast, economic policy uncertainty shocks are associated with a substantial fall in consumer sentiment, leading to weaker demand for goods and services.

Climate policy uncertainty has significant implications not only at the macroeconomic level but also at the firm level. Using the universe of U.S. listed firms, we find that climate policy uncertainty shocks lead to marked declines in sales, employment, investment, and R&D, indicating that firms perceive climate policy uncertainty as a material source of financial risk. On average, firm-level sales and employment fall by about 1 and 0.7 percent, respectively, while investment and R&D expenses decline by 2 and 1.6 percent.

The firm-level responses are strongly shaped by exposure to climate risk. Firms respond more strongly to climate policy uncertainty when their exposure to climate change is high. A one-standard-deviation increase in a firm's relative exposure leads to an additional 0.8 percent decline in investment and a 0.3 percent reduction in R&D expenses. Exploiting within-firm time-series variation also allows us to flexibly control for confounding common aggregate and sector-specific factors, as well as a firm-level climate policy sentiment index that nets out exposure to first-moment policy changes; our results remain robust to these additional controls.

Finally, we document meaningful sectoral heterogeneity in the response to climate policy uncertainty. While most sectors experience a decline in investment, the mining, quarrying, oil and gas extraction, and utilities sectors display a positive investment response, at least in the short term. Thus, we do find evidence consistent with a green paradox at the micro level: climate policy uncertainty may incentivize fossil-related sectors to accelerate brown projects ahead of potentially stricter regulation in the future. At the same time, R&D spending falls particularly sharply in these sectors, and total factor productivity declines persistently both in the aggregate and at the firm level, indicating that climate policy uncertainty exacerbates transition costs through misallocative forces.

A comprehensive series of sensitivity checks indicate that our results are robust along a number of dimensions, including the measurement of climate policy uncertainty, the identification strategy, the estimation technique, and the model specification. Importantly, our results are robust to estimating the dynamic causal effects directly using local projections, relaxing the assumptions regarding invertibility and the dynamic VAR structure.

Related literature. A burgeoning literature studies the effects of climate policy *actions* (see Bilal and Stock, 2025, for a survey). There is substantial evidence that national climate policies reduce emissions (Martin, De Preux, and Wagner, 2014; Andersson, 2019; Colmer et al., 2025). The macroeconomic effects of carbon pricing are more mixed, with estimates for European and Canadian carbon taxes ranging from modest to more pronounced depending on policy design (Metcalf, 2019; Bernard and Kichian, 2021; Kapfhammer, 2023; Känzig, 2025; Känzig and Konradt, 2024). Despite these short-run trade-offs, recent estimates of a high social cost of carbon underscore the importance of effective and predictable climate policy (Burke et al., 2023; Bilal and Känzig, 2024).

However, in many countries, including the U.S., implementing national climate policy initiatives has proven challenging. As a result, *uncertainty* about the future path of climate policy has become an increasingly salient concern. In pioneering work, Engle et al. (2020) construct a climate news index using textual data. Using a similar approach, Gavriilidis (2021)—whose analysis this paper supersedes—and Basaglia et al. (2022) develop news-based measures of climate policy uncertainty. Subsequent work has extended these approaches to construct cross-country measures for OECD economies (Berestycki et al., 2022) or indices capturing the direction or concerns about climate policy uncertainty (Basaglia et al., 2025; Marotta, Pagliari, and Winter, 2025). These studies document important effects, primarily at the firm or sectoral level, highlighting the role of policy-related uncertainty for investment and innovation decisions. Sautner et al. (2023) provides complementary firm-level evidence, measuring firms' exposure to climate change using earnings conference calls.

A related literature considers measures of *environmental policy uncertainty*. Noailly, Nowzohour, and Van Den Heuvel (2022) and Palikhe, Schaur, and Sims (2024) construct indices that capture uncertainty about environmental regulation, rather than climate policy. While related, these measures reflect a different concept. Consistent with this distinction, the resulting indices are only moderately correlated with measures of climate policy uncertainty.

Relative to these literatures, our paper focuses on the aggregate, macroeconomic effects of climate policy uncertainty and proposes a new approach to identification. While existing work has made notable progress in measuring climate and environmental policy uncertainty, identification is more challenging at the macro level.[1] In firm-level settings, rich fixed effects can absorb many confounding factors. This is not feasible at the aggregate level, making concerns about endogeneity and confounding policy news more acute. To address this, we construct a narrative, event-based instrument that isolates exogenous variation in climate policy uncertainty.

Methodologically, our paper builds on the influential literature studying the role of uncertainty for economic and financial fluctuations (see Bloom, 2014, for a survey). We follow the prominent news-based approach to proxy for uncertainty (Saiz and Simonsohn, 2013; Baker, Bloom, and Davis, 2016; Caldara and Iacoviello, 2022, among others). A key challenge in this literature is to disentangle changes in uncertainty from changes in expected policy. Recent work has made progress along this dimension using textual approaches (Hassan et al., 2019; Caldara et al., 2020). We complement these approaches with a narrative, event-based strategy that exploits a distinctive feature of climate policy: policy actions can either raise or resolve uncertainty, so that first- and second-moment effects need not move together. Our finding that climate policy uncertainty transmits differently from standard policy uncertainty shocks aligns with Gambetti et al. (2023), who emphasize that the effects of uncertainty depend on its underlying source.

Finally, we connect to a theoretical literature studying uncertainty in climate economics. Fried, Novan, and Peterman (2021) show in a dynamic general equilibrium

[1] A few studies also look at macroeconomic outcomes (Mourelon, 2024; Marotta, Pagliari, and Winter, 2025), but do not address the identification concerns we focus on; for instance, Mourelon (2024) uses the index of Gavriilidis (2021) in a simple recursive VAR, as we did in an earlier version of this project (Gavriilidis, Känzig, and Stock, 2023).

model that climate policy uncertainty reduces emissions by depressing output and shifting investment toward cleaner technologies, but that similar emissions reductions could be achieved at lower cost under a predictable carbon tax. More broadly, Barnett, Brock, and Hansen (2022) and Barnett et al. (2025) emphasize the role of uncertainty—particularly regarding damages and the transition—in shaping economic outcomes and optimal policy. We contribute to this literature by providing new empirical targets for quantitative climate policy models.

Outline. The remainder of this paper is organized as follows. Section 2 discusses our measurement of climate policy uncertainty based on newspaper coverage and introduces and validates our climate policy uncertainty index. In Section 3, we propose a new instrument to estimate the effects of climate policy uncertainty shocks and discuss our econometric framework and specification. Section 4 presents the results on the macroeconomic impact of climate policy uncertainty, including a comparison to economic policy uncertainty, a monetary policy counterfactual, and a series of sensitivity checks. Section 5 studies the firm-level and sectoral impacts. Section 6 concludes.

2. Measuring climate policy uncertainty

Measuring uncertainty is a difficult task. In this section, we outline our definition of climate policy uncertainty, detail its measurement, and discuss the validation of our approach.

2.1. Defining climate policy uncertainty

We define climate policy uncertainty (CPU) as the lack of clarity and predictability surrounding government actions to address climate change. Our focus is on current and future climate policy with national significance. Uncertainty about climate policy can arise from various sources, including political debate around proposed policy changes, uncertainty about implemented policies due to political or legal challenges, or regulatory ambiguity stemming from the complexity of climate policy design. This uncertainty encompasses questions about who will make key policy decisions, what actions will ultimately be taken and when, and how these actions—or the lack thereof—will impact the economy.

While our notion of climate policy uncertainty is broad, we constrain our definition along two dimensions. First, we adopt a macro perspective and focus on climate policy with *national* significance. This means that we largely abstract from local policy uncertainty at the state, county, or municipal level. This decision is motivated by the fact that while the impacts of climate change can vary widely locally, the solutions are predominantly global in nature and are most likely to be shaped by national or supranational policies. That said, we do include landmark state-level policies when they are sufficiently large or comprehensive to plausibly generate macroeconomic effects and when they meaningfully influence the national policy debate.

Second, we specifically focus on uncertainty related to *climate policy*, abstracting from uncertainty surrounding environmental regulations unrelated to climate change (such as pollution control measures) or non-climate-related energy market regulations (such as policies aimed at confronting energy shortages). This distinction is important because such policies tend to be narrower in scope or more closely tied to short-run economic conditions—for example, fluctuations in energy prices or geopolitical developments—rather than to long-run climate objectives. Excluding these sources of uncertainty allows us to isolate the macroeconomic effects of uncertainty that is specific to the climate policy domain.

2.2. Measurement based on newspaper coverage

We measure climate policy uncertainty based on newspaper coverage addressing uncertainty about the path of climate policy. The information contained in newspapers has been shown to be particularly useful to measure policy uncertainty (Baker, Bloom, and Davis, 2016; Al-Thaqeb and Algharabali, 2019). We build on this approach to construct an uncertainty index specific to climate policy. The basic idea is to proxy climate policy uncertainty by the frequency at which uncertainties about topics related to climate policy are covered in the press.

Our sample consists of the text from 7.87 million news articles published in the print editions of leading American newspapers from the mid-1980s—when climate policy became relevant—through the present. Our main set of newspapers includes the *New York Times* (NYT), the *Wall Street Journal* (WSJ), the *Washington Post* (WaPo), and the *Los Angeles Times* (LAT). We select these newspaper outlets because they provide comprehensive and systematic coverage of national climate policy developments. Given the specialized nature of climate policy, such coverage is often more limited in regional newspapers. However, our results are robust to using a larger set of newspapers as in Baker, Bloom, and Davis (2016). Our index measures, for each month, the number of articles discussing uncertainty about climate policy, divided by the total number of published articles. The

Figure 1: Climate policy dictionary by category

(a) Climate change (b) Policy (c) Climate policy

Notes: Each panel shows the most common concepts in the climate change, policy, and climate policy dictionaries derived from the climate policy news corpus. The size of the concept reflects its frequency across the corpus.

standardization and aggregation methodology, detailed below, takes care of the overall variation in the number of articles across newspapers and time.

To identify articles that cover climate policy uncertainty, we use a dictionary-based approach (Baker, Bloom, and Davis, 2016; Caldara and Iacoviello, 2022). The idea is to specify a dictionary of words whose occurrence in newspaper articles is associated with the coverage of topics related to climate policy uncertainty. This is a simple and transparent way to proxy the extent of climate policy uncertainty.

Our approach relies on three distinct dictionaries covering *climate change*, *policy*, and *uncertainty* topics. In addition, we construct a *climate policy* dictionary that contains concepts spanning both climate change and policy. An article is classified as discussing climate policy uncertainty if it contains at least one term from each of the *climate change*, *policy*, and *uncertainty* dictionaries, or if it contains at least one term from both the *climate policy* and *uncertainty* dictionaries.

To construct the dictionaries, we rely on a corpus of news articles from agencies specialized in climate policy reporting, including *Inside Climate News*, *Inside EPA*, and *Washington Week (Energy)*. Our climate policy news corpus dates back to the early 2000s and comprises around 26,500 news articles.

We then follow a method similar to Aruoba and Drechsel (2024) to select the concepts for the dictionaries. First, we pre-process the climate policy news corpus by splitting contractions and tokenizing the text. We then retrieve unigrams, bigrams, and trigrams (*n*-grams) from the corpus, defined for our purposes as follows. Unigrams are individual words and bigrams are two adjacent words that do not contain stop words. Trigrams are three adjacent words that do not start or end with a stop word. For instance, "... greenhouse gas emission ..." gives us one trigram ("greenhouse gas emission"), two bigrams ("greenhouse gas" and "gas emission"), and three unigrams ("greenhouse", "gas", and "emission") while "... cap and trade ..." gives us one trigram ("cap and trade") and two unigrams ("cap" and "trade").

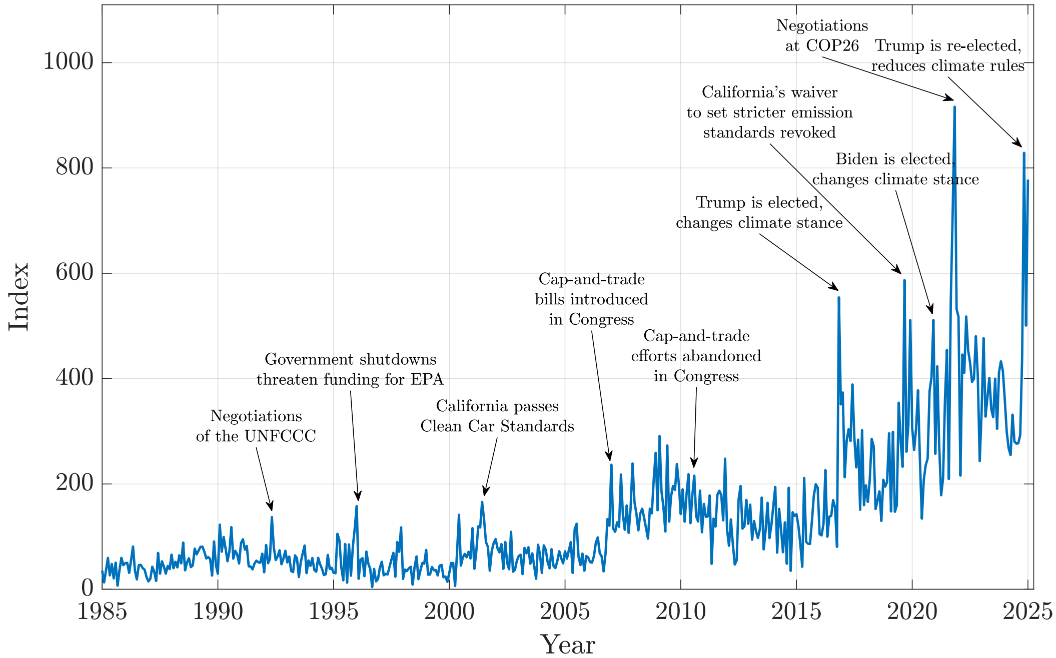
Our climate policy news corpus contains roughly 57,900 unigrams, 959,300 bigrams, and 1,636,200 trigrams. In the next step, we rank each set of *n*-grams by their total frequency of occurrence in our corpus. Starting from the most frequent *n*-grams and moving down the ranking, we select those concepts relevant to *climate change*, *policy*, or *climate policy*.[2] We apply this procedure separately to trigrams, bigrams, and unigrams. When selecting concepts, we ensure that each term is sufficiently specific and unambiguous when considered in isolation. This is important to avoid identifying false positives, which is of particular concern with unigrams. For instance, the concept "climate" is not specific enough as it can relate to other contexts such as "business climate". Finally, we augment the dictionaries with some additional concepts, based on our definition of climate policy uncertainty—for instance, to ensure that we also include relevant concepts that were more salient before the 2000s, prior to the start of our climate policy news corpus. The most common concepts in our climate, policy, and climate policy dictionaries are illustrated in Figure 1, where the size of each concept reflects its frequency in the climate policy news corpus.

For the *uncertainty* dictionary, we rely on the established approach in the literature and include variations of the word "uncertain" (Baker, Bloom, and Davis, 2016). For more information on the construction of our dictionaries, see Appendix A.1.

Next, we apply these dictionaries to our newspaper corpus to identify articles discussing climate policy uncertainty. Based on the identified articles, we construct a climate policy uncertainty index, CPU_t. To construct the index, we count, for each newspaper, the number of climate policy uncertainty articles in each month, scaled by the total number of articles in that month: $s_{i,t} = n_{i,t}^{\text{cpu}} / n_{i,t}^{\text{tot}}$ for $i \in \{\text{NYT}, \text{WSJ}, \text{WaPo}, \text{LAT}\}$. We standardize each monthly newspaper-level series to unit standard deviation over the period 1985 to 2019 and then construct an average across all the newspapers by month: $\text{CPU}_t = \frac{1}{4} \sum_i s_{i,t} / \sigma_i^s$, where σ_i^s is the standard deviation of $s_{i,t}$ over the period 1985 to 2019. Finally, we normalize the averaged series to have a mean of 100 between 1985 and 2019.

[2] Multiple authors independently carried out this selection and discussed disagreements. We stop at a generous lower bound of the frequency ranking.

Figure 2: The climate policy uncertainty index



Notes: Climate policy uncertainty index based on newspaper coverage in the *New York Times*, the *Wall Street Journal*, the *Washington Post*, and the *Los Angeles Times*.

2.3. The climate policy uncertainty index

Figure 2 shows the constructed climate policy uncertainty index, from 1985 until 2025. At the beginning of our sample, uncertainty about climate policy was at a relatively low level. However, climate policy uncertainty began to increase in the late 1980s, following the U.S. ratification of the Montreal Protocol, and remained elevated through the early to mid-1990s, when the first Energy Policy Act was passed. There were also some notable spikes during this period—for instance, in 1992, surrounding the adoption of the United Nations Framework Convention on Climate Change (UNFCCC). At the end of 1995, a series of government shutdowns over budget disputes threatened funding for the Environmental Protection Agency, increasing uncertainty about climate regulations. Afterwards, climate policy uncertainty remained subdued until the early 2000s, when President Bush withdrew from the the Kyoto Protocol and proposed a set of alternative climate and energy policies. Around the same time, California passed the Pavley regulation, the first law in the nation to regulate vehicle emissions—further contributing to uncertainty about climate policy.

In 2007, climate policy uncertainty increased sharply amid the introduction of several climate and energy bills, including prominent efforts to establish cap-and-trade legislation—such as the American Clean Energy and Security Act proposed by Henry Waxman and Ed Markey. Uncertainty began to subside in 2010, once it became evident that legislative initiatives to limit greenhouse gas emissions lacked majority support. Climate policy uncertainty remained at lower levels until the end of 2015, when the Paris Climate Agreement was adopted at the 21st Conference of the Parties (COP21).

In November 2016, following Donald Trump's victory in the presidential elections, climate policy uncertainty surged to unprecedented levels. During the first months of the Trump presidency, uncertainty remained at historically high levels as the administration dramatically shifted the stance on climate policy and announced the withdrawal from the Paris Climate Agreement. In 2019, climate policy uncertainty spiked again. Early in the year, momentum was building for initiatives to reduce greenhouse gas emissions, highlighted by the introduction of the Green New Deal Resolution by Alexandria Ocasio-Cortez and Ed Markey in February. However, these efforts faced significant setbacks later that year when the Trump administration revoked California's long-standing authority to set stricter vehicle emissions standards, effectively limiting states' ability to exceed national regulations. This period marked the beginning of a new era of elevated climate policy uncertainty.

The following years were characterized by stark policy shifts and reversals. After his election in November 2020, Joe Biden moved quickly to undo key elements of the Trump administration's climate agenda, rejoining the Paris Agreement and reinstating federal support for climate mitigation. This was followed by the passage of major climate and clean-energy legislation, most notably the Infrastructure Investment and Jobs Act and the Inflation Reduction Act, which substantially expanded federal involvement in climate policy. While these measures marked a decisive break from prior policy, they also heightened uncertainty by reinforcing expectations that U.S. climate policy would remain contingent on electoral outcomes. These expectations were reinforced by Donald Trump's return to office, which triggered another round of policy reversals, including the rollback of key regulatory climate actions and the withdrawal from international climate commitments, leading to a sharp increase in climate policy uncertainty.[3]

[3] Part of the increase in the index in the later part of the sample may reflect increased media attention to climate policy. Appendix D.2.2 shows that the increase is less pronounced when normalizing the index by climate policy coverage. Importantly, our identification strategy does not rely on the gradual rise in climate policy uncertainty over time, and our results are robust to using this alternative index.

2.4. Validation

We conduct a series of validation exercises to assess the reliability of the index. First, as illustrated above, we confirm that periods of historically high climate policy uncertainty correspond to spikes in our climate policy uncertainty index. Second, we perform two audits on a subset of articles identified as covering climate policy—a human audit and one using a large language model (LLM), see Appendix A.2.3 for more information. False positives are of particular concern when using text-search methods; our audits indicate that, due to the specificity of our dictionary terms, only a small number of articles are false positives. Third, we analyze the sensitivity of our results to alternative classification strategies. We consider two alternative dictionary-based climate policy uncertainty indices: one based on a broader version of our dictionary, and the original index proposed by Gavriilidis (2021), which is even less restrictive in its choice of concepts. In addition, we construct an alternative LLM-based CPU index by applying the `gpt-4o-mini` model to the full sample of narrow climate policy articles (see Appendix D.2.3). The alternative indices are highly correlated with our baseline measure, with correlations of 0.8 and above, and the estimated responses remain robust across specifications. This evidence suggests that our dictionary-based approach reliably captures variation in climate policy uncertainty, while our instrumental-variable approach further alleviates concerns about measurement error in the index.

Table 1 presents pairwise correlations of our index with a range of related measures. Our index correlates meaningfully with alternative measures of climate policy uncertainty (Gavriilidis, 2021; Basaglia et al., 2022). We improve on these measures by introducing a disciplined and transparent approach to keyword selection, together with a comprehensive validation framework that directly evaluates classification performance. By contrast, the index is only moderately correlated with measures of environmental policy uncertainty (Noailly, Nowzohour, and Van Den Heuvel, 2022; Palikhe, Schaur, and Sims, 2024) and with the regulation subindex from Baker, Bloom, and Davis (2016), which also includes environmental regulations. This suggests that climate policy uncertainty captures a distinct concept. In terms of precision, our approach compares favorably to existing measures. For instance, Noailly, Nowzohour, and Van Den Heuvel (2022) report a precision of 56 percent compared to 80 percent for our baseline index.[4]

Our climate policy uncertainty index is only weakly correlated with other uncertainty measures in the literature. The correlation with the VXO is -0.08 and the correlation with

[4] Basaglia et al. (2022) report a precision comparable to our baseline index, but it is unclear how articles are sampled and evaluated, complicating a direct comparison.

Table 1: Correlations with other indices

Index	Method	ρ	p-value	Sample
Panel A: Climate policy uncertainty indices				
Our baseline index	Dictionary-based	1.00	0.00	1985M01-2019M12
Our broad index	Dictionary-based	0.93	0.00	1985M01-2019M12
Our LLM index	LLM-based	0.84	0.00	1985M01-2019M12
Gavriilidis (2021)	Dictionary-based	0.79	0.00	1987M04-2019M12
Basaglia et al. (2025)	Dictionary-based	0.74	0.00	1990M01-2019M12
Panel B: Environmental policy uncertainty indices				
Noailly et al. (2022)	ML-based	0.05	0.35	1990M01-2019M03
Palikhe et al. (2024)	Dictionary-based	0.28	0.00	1985M01-2019M12
Baker et al. (2016) EPU regulation subindex	Dictionary-based	0.33	0.00	1985M01-2019M12
Panel C: Other uncertainty indices				
Baker et al. (2016) EPU	Dictionary-based	0.36	0.00	1985M01-2019M12
Financial uncertainty (VXO)	Dictionary-based	-0.08	0.12	1985M01-2019M12
Caldara & Iacoviello (2018) geopolitical risk	Dictionary-based	-0.05	0.27	1985M01-2019M12

Notes: Pairwise correlations between our climate policy uncertainty index and a range of related indices. Panel A compares our baseline CPU index to alternative climate policy uncertainty measures; Panel B to environmental policy uncertainty indices; and Panel C to broader uncertainty indicators. The reported coefficient ρ denotes the Pearson correlation. P-values correspond to tests of the null hypothesis of zero correlation.

the geopolitical risk index by Caldara and Iacoviello (2022) is -0.05. Unsurprisingly, climate policy uncertainty correlates somewhat more strongly with economic policy uncertainty, as measured by the Baker, Bloom, and Davis (2016) index, with a correlation coefficient of 0.36. This is expected, given that climate policy uncertainty is a particular dimension of broader economic and policy uncertainty. These moderate correlation coefficients illustrate that the climate policy uncertainty index captures variation distinct from other dimensions of policy uncertainty. Indeed, we will show in Section 4 that controlling for economic policy uncertainty and other uncertainty measures leaves our results virtually unchanged.

3. Identifying climate policy uncertainty shocks

Identifying the macroeconomic effects of climate policy uncertainty involves three central challenges. First, movements in climate policy uncertainty may not be exogenous, as policymakers adjust their climate stance in response to economic developments. Second, climate policy uncertainty may be confounded with shifts in broader economic or political uncertainty. Third, observed movements in uncertainty may reflect not only second-moment shocks but also changes in the expected direction of policy (first-moment shocks).

We address these challenges by constructing an event-based instrument for U.S. climate policy uncertainty that combines a narrative identification of major climate policy events with high-frequency newspaper coverage.

3.1. A new instrument based on major climate policy events

We compile a comprehensive narrative record of major U.S. climate policy events between 1985 and 2019. The events span legislative, regulatory, executive, and judicial actions and are selected to capture episodes that plausibly altered uncertainty about U.S. climate policy while being driven primarily by climate-related or ideological considerations rather than by contemporaneous macroeconomic conditions. We focus on the pre-2020 period to avoid large outliers and potential confounding effects associated with the Covid-19 pandemic; later years are considered in robustness checks in Appendix D.2.

Climate policy events and their media impact. Drawing on official sources, such as government administration websites, congressional records, and regulatory agency releases, we identify 146 climate policy uncertainty events. Table 2 provides a brief classification of the events we identify. In selecting events, we adopt an agnostic approach and seek to capture all relevant stages of the policy cycle. For instance, in the case of legislative actions, we trace measures from their initial introduction through to formal presidential approval or, where applicable, to the point at which they stall or are rejected. Importantly, we identify events that both generate and resolve climate policy uncertainty (see Appendix B.1 for more details).

Table 2: Classification of climate policy uncertainty events

Event Type	Count
Advocacy	2
International agreements, treaties, and conventions	20
Judicial action	6
Legislative action	56
Presidential action	22
Regulatory action	40
Total	**146**

Notes: Overview of climate policy uncertainty events and their classification into different event types.

The identified events include major legislative initiatives such as the Waxman–Markey cap-and-trade bill, which passed the House but failed in the Senate; repeated shifts in U.S. participation in the Paris Climate Agreement, including entry, withdrawal, and re-entry across administrations; and regulatory reversals surrounding California's waiver to set stricter vehicle emission standards than federal law. In Section 4.3 we show that our results are not driven by any individual event or category of events.

For each identified climate policy uncertainty event, we quantify its impact using high-frequency newspaper coverage. Specifically, for each newspaper i we count the number of climate-policy articles n_i^{cp} published on the event day and the following day, normalized by that newspaper's total monthly coverage, in the spirit of Baker, Bloom, and Terry (2024). To account for anticipatory effects, we subtract the number of climate-policy articles published in the two days preceding the event $n_{i,\text{Event}} = \sum_{d=0}^{1} n_{i,d}^{\text{cp}} - \sum_{d=-2}^{-1} n_{i,d}^{\text{cp}}$. The resulting series reflects unexpected shifts in climate policy reporting around policy events that are plausibly orthogonal to macroeconomic conditions.

Isolating uncertainty from policy news. A key difficulty in the uncertainty literature is disentangling changes in uncertainty from changes in the expected direction of policy. Climate policy provides a distinctive setting in which these two need not move together: policy actions that tighten or loosen regulation may either resolve or exacerbate uncertainty depending on their credibility and permanence, unlike in many other settings where adverse news and higher uncertainty typically move in lockstep.

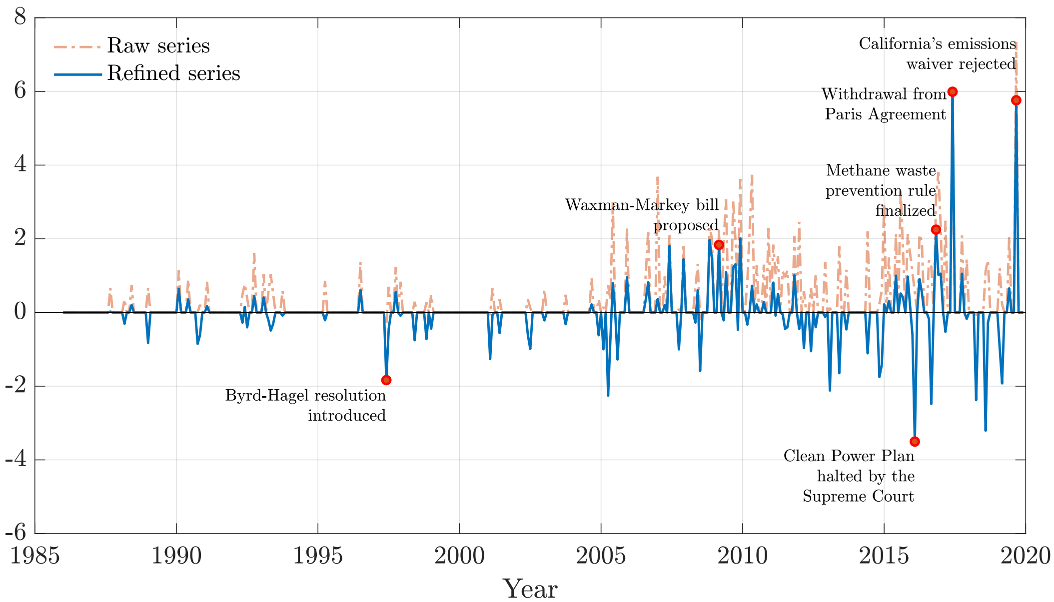
To separate uncertainty from policy news, we proceed in two steps. First, we use our narrative approach to construct a measure of policy stringency. Based on the content of each legislative, regulatory, or executive action, we classify events as signaling a tightening, loosening, or no change in the policy stance, thereby obtaining a transparent event-level measure of policy stringency.

Second, we purge the reporting intensity of the component explained by these shifts in policy stringency. Formally, we estimate

$$n_{i,\text{Event}} = \alpha_i + \beta_i \times \text{Stringency}_{\text{Event}} + \text{Uncertainty}_{\text{i, Event}} \tag{1}$$

and measure shifts in climate policy uncertainty as the residual from this regression. Intuitively, this step removes the portion of media coverage driven by directional policy news—such as an unexpected tightening or loosening of regulation—leaving residual variation that plausibly captures shifts in uncertainty about future climate policy. This approach is similar in spirit to Hassan et al. (2019), but operates at the event level, where

Figure 3: The event-based climate policy uncertainty series



Notes: Event-based climate policy uncertainty series (solid blue line), against the raw climate policy reporting intensity (red dashed line). Positive values indicate increases in uncertainty that cannot be explained by changes in expected policy stringency, while negative values indicate the resolution of previously elevated uncertainty.

the direction of policy news is directly observed.[5]

We implement this procedure for each newspaper, standardize the resulting event-level series, and average across outlets. We then aggregate to the monthly frequency by summing across all events within a month, assigning zero to months with no events. For more details, see Appendix B.3.

Figure 3 plots the event-based climate policy uncertainty series. The dashed red line shows the raw reporting intensity around climate policy events, while the solid blue line shows the refined series after purging first-moment policy news. Positive values indicate increases in uncertainty that cannot be explained by changes in expected policy stringency, while negative values indicate the resolution of previously elevated uncertainty.

Several prominent episodes illustrate how the series captures economically meaningful shifts in climate policy uncertainty. In June 1997, the Byrd–Hagel Resolution passed

[5]In our baseline specification, the stringency measure is purely directional, with each event coded as a tightening (+1), a loosening (-1), or neutral (0) based on the narrative content of the policy action. This parsimonious classification provides a transparent way to capture the first moment of climate policy news. In sensitivity analyses, we allow for richer measures that also incorporate the magnitude of policy changes, for example by assigning larger weights to more binding or consequential actions or by scaling stringency with the intensity of media coverage. Our results are robust to all of these alternative constructions, see Appendix Figure D.3.

the U.S. Senate, effectively ruling out U.S. participation in international agreements such as the Kyoto Protocol that imposed binding targets only on developed countries. This event reduced uncertainty by clarifying the U.S. position on international climate commitments. In contrast, uncertainty rose sharply in March 2009 with the introduction of the Waxman–Markey American Clean Energy and Security Act, which proposed a national cap-and-trade system but faced an uncertain legislative path. Uncertainty remained elevated until 2010, when comprehensive federal climate legislation was effectively abandoned in the Senate.

In February 2016, uncertainty further declined when the Supreme Court stayed the Clean Power Plan, temporarily halting the EPA's effort to regulate emissions from power plants and clarifying the near-term regulatory outlook. Later that year, uncertainty rose again when the methane waste prevention rule was finalized, reintroducing ambiguity about the future scope of federal climate regulation.

International and state-level actions also play an important role. Uncertainty increased in June 2017 when the United States announced its withdrawal from the Paris Climate Agreement, creating ambiguity about the country's long-run climate commitments. It rose again in September 2019 when the federal government revoked California's waiver to set stricter vehicle emission standards, casting doubt on the future of sub-national climate policy. These episodes illustrate how the series captures shifts in uncertainty arising from legislative, regulatory, and international dimensions of U.S. climate policy.

Diagnostics. We perform a number of diagnostic checks on the instrument following Ramey (2016), in particular with regards to autocorrelation, forecastability, and correlation with other structural shocks. Because climate policy uncertainty events are concentrated in the late 2000s and from mid-2010 onwards, the series is weakly serially correlated. However, our results are robust to using a residualized version of the instrument purged from autocorrelation as proposed in Miranda-Agrippino and Ricco (2021a), see Appendix Figure D.4. We also find little evidence that macroeconomic or financial variables have any power in forecasting the instrument. For all variables considered, the p-values for the Granger causality test are far above conventional significance levels, with the joint test having a p-value of 0.95. Finally, we show that the instrument is uncorrelated with other structural shock measures from the literature, including uncertainty, oil, productivity, news, monetary policy, fiscal policy, and financial shocks. Overall, this evidence supports the validity of the climate policy uncertainty instrument. The corresponding figures and tables can be found in Appendix D.1.

3.2. Econometric framework

To estimate the dynamic causal effects of climate policy uncertainty, we rely on VAR techniques. In this way, we estimate the aggregate effect of climate policy uncertainty, including any general equilibrium adjustments. Our starting point is the following structural vector moving-average representation:

$$\mathbf{y}_t = \mathbf{B}(L)\mathbf{S}\boldsymbol{\varepsilon}_t, \tag{2}$$

where $\boldsymbol{\varepsilon}_t$ is a vector of mutually uncorrelated structural shocks driving the economy, $\mathbf{B}(L) \equiv \mathbf{I} + \mathbf{B}_1 L + \mathbf{B}_2 L^2 + \dots$ is a matrix lag polynomial, and $\mathbf{S}$ is the structural impact matrix.

Assuming that the vector-moving average process (2) is invertible, it admits the following VAR representation:

$$\mathbf{A}(L)\mathbf{y}_t = \mathbf{S}\boldsymbol{\varepsilon}_t = \mathbf{u}_t, \tag{3}$$

where $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations with variance-covariance matrix $\mathrm{Var}(\mathbf{u}_t) = \boldsymbol{\Sigma}$ and $\mathbf{A}(L) \equiv \mathbf{I} - \mathbf{A}_1 L - \dots$ is a matrix lag polynomial. By definition, the structural shocks are mutually uncorrelated, i.e. $\mathrm{Var}(\boldsymbol{\varepsilon}_t) = \boldsymbol{\Omega}$ is diagonal. From the invertibility assumption (3), we get the standard covariance restrictions $\boldsymbol{\Sigma} = \mathbf{S}\boldsymbol{\Omega}\mathbf{S}'$.

Truncating the VAR to order p, we can estimate the model using standard techniques and recover an estimate of $\mathbf{A}(L)$ and $\boldsymbol{\Sigma}$.

We are interested in characterizing the causal impact of a single climate policy uncertainty shock. Without loss of generality, let us denote the climate policy uncertainty shock as the first shock in the VAR, $\varepsilon_{1,t}$. Our aim is to identify the structural impact vector $\mathbf{s}_1$, which corresponds to the first column of $\mathbf{S}$. To identify the shock, we will rely on event-based climate policy uncertainty series.

External instrument approach. Given the instrument z_t, which in our case is the event-based climate policy uncertainty series, identification can be achieved using the SVAR-IV method (Stock, 2008). The instrument, z_t, is a valid instrument if it is correlated with the climate policy uncertainty shock, $\varepsilon_{1,t}$, but uncorrelated with all other structural shocks,

$\boldsymbol{\varepsilon}_{2:n,t}$. Formally, we require:

$$\mathbb{E}[z_t \varepsilon_{1,t}] = \alpha \neq 0 \tag{4}$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{5}$$

where assumption (4) is the relevance requirement and assumption (5) is the exogeneity condition. These assumptions, in combination with the invertibility requirement (3), identify $\mathbf{s}_1$ up to sign and scale:

$$\mathbf{s}_1 \propto \frac{\mathbb{E}[z_t \mathbf{u}_t]}{\mathbb{E}[z_t \mathrm{u}_{1,t}]}, \tag{6}$$

provided that $E[z_t \mathrm{u}_{1,t}] \neq 0$.[6] We implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\hat{\mathbf{u}}_t$ on $\hat{\mathrm{u}}_{1,t}$ using z_t as the instrument. To conduct inference, we use a residual-based moving block bootstrap, as proposed by Jentsch and Lunsford (2019).

Short-run restrictions. Alternatively, we identify a climate policy uncertainty shock using short-run timing restrictions (Sims, 1980). The identifying assumption is that climate policy uncertainty only responds to macroeconomic developments with a lag of a month. This can be implemented by ordering the climate policy uncertainty index first in a recursive VAR, where the structural impact vector is given by $s_1 = [\mathrm{chol}(\boldsymbol{\Sigma})]_{\cdot,1}$. We apply the same strategy to identify economic policy uncertainty shocks, as in Baker, Bloom, and Davis (2016).

Local projections. The VAR approach is efficient and delivers sharp inference, but it relies on two potentially restrictive assumptions. First, invertibility requires that the model incorporates all relevant information needed to recover the structural shocks of interest. Second, the dynamic VAR structure assumes that a finite-order VAR provides a good approximation to the data-generating process.

To assess how restrictive these assumptions are, we consider two additional estimators. In the first, we only relax the dynamic VAR structure while maintaining the identified climate policy uncertainty shock. Specifically, we extract the climate policy uncertainty shock from the monthly VAR as $\varepsilon_{1,t} = \mathbf{s}_1' \boldsymbol{\Sigma}^{-1} \mathbf{u}_t$ (see Stock and Watson, 2018), and

[6] To be more precise, the VAR does not have to be fully invertible for identification with external instruments. As Miranda-Agrippino and Ricco (2023) and Stock and Watson (2018) show, it suffices if the shock of interest is invertible in combination with a limited lead-lag exogeneity condition.

estimate impulse responses using local projections à la Jordà (2005):

$$y_{i,t+h} = \alpha^i_{h,0} + \theta^i_h \varepsilon_{1,t} + \beta^i_{h,1} y_{i,t-1} + \ldots + \beta^i_{h,p} y_{i,t-p} + \nu_{i,t,h}, \tag{7}$$

where $y_{i,t+h}$ is the outcome variable of interest and h denotes the impulse response horizon. This approach relaxes the VAR's dynamic restrictions by directly estimating the impulse responses, while still assuming (partial) invertibility of the VAR used to recover the shock.

An additional advantage of this approach is that it allows us to estimate responses for variables observed at lower frequencies, such as quarterly or annual series. In these cases, we aggregate the shock $\varepsilon_{1,t}$ by summing over the respective months before running the local projections. This mitigates the loss of power that often arises when external instruments are aggregated to lower frequencies (Nakamura and Steinsson, 2018).

Second, we estimate the dynamic causal effects using a local projections–instrumental variables (LP–IV) approach (Jordà, Schularick, and Taylor, 2015; Ramey, 2016). This specification dispenses with the invertibility assumption altogether and directly estimates the causal effects of a climate policy uncertainty shock based on:

$$y_{i,t+h} = \alpha^i_h + \theta^i_h y_{1,t} + \boldsymbol{\beta}^{i\prime}_h \mathbf{x}_{t-1} + \nu_{i,t,h}, \tag{8}$$

using z_t as an instrument for $y_{1,t}$. Here, $y_{i,t+h}$ is again the outcome variable of interest, $y_{1,t}$ is the endogenous regressor, $\mathbf{x}_{t-1}$ is a vector of controls. We include the same controls as in the VAR and conduct inference using the lag-augmentation procedure of Montiel Olea and Plagborg-Møller (2020), see also Montiel Olea et al. (2024, 2025).

For identification, this approach requires in addition to (4)-(5) that the instrument be orthogonal to leads and lags of the structural shocks,

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{t+j}] = \mathbf{0}, \quad \text{for } j \neq 0, \tag{9}$$

but, in return, allows us to dispense with both invertibility and the parametric VAR dynamics.

3.3. Model specification

Our baseline specification includes six variables: the climate policy uncertainty index, industrial production, the unemployment rate, a commodity price index, the consumer price index (CPI), and a short-term interest rate proxying the stance of monetary policy.

We use the 3-month Treasury bill as the policy rate, striking a balance between concerns about the zero lower bound and its relevance for monetary policy. However, the results are robust to using the 1-year rate or a shadow federal funds rate. As the commodity price index we use the Goldman Sachs commodity index. Controlling for forward-looking variables such as commodity prices is important to alleviate concerns about non-invertibility. For more information about the data and its sources, see Appendix C.1.

The data is monthly and our sample spans the period from 1985, when our climate policy uncertainty index becomes available, through 2019, ending before the onset of the Covid-19 pandemic. We include the unemployment rate and the short-term rate in levels, all other variables enter in log-levels. The lag order is set to 12, as is customary with monthly data, and in terms of deterministics we include a constant and a linear trend. However, the results turn out the be robust with respect to all of these choices.

4. The effect on the macroeconomy

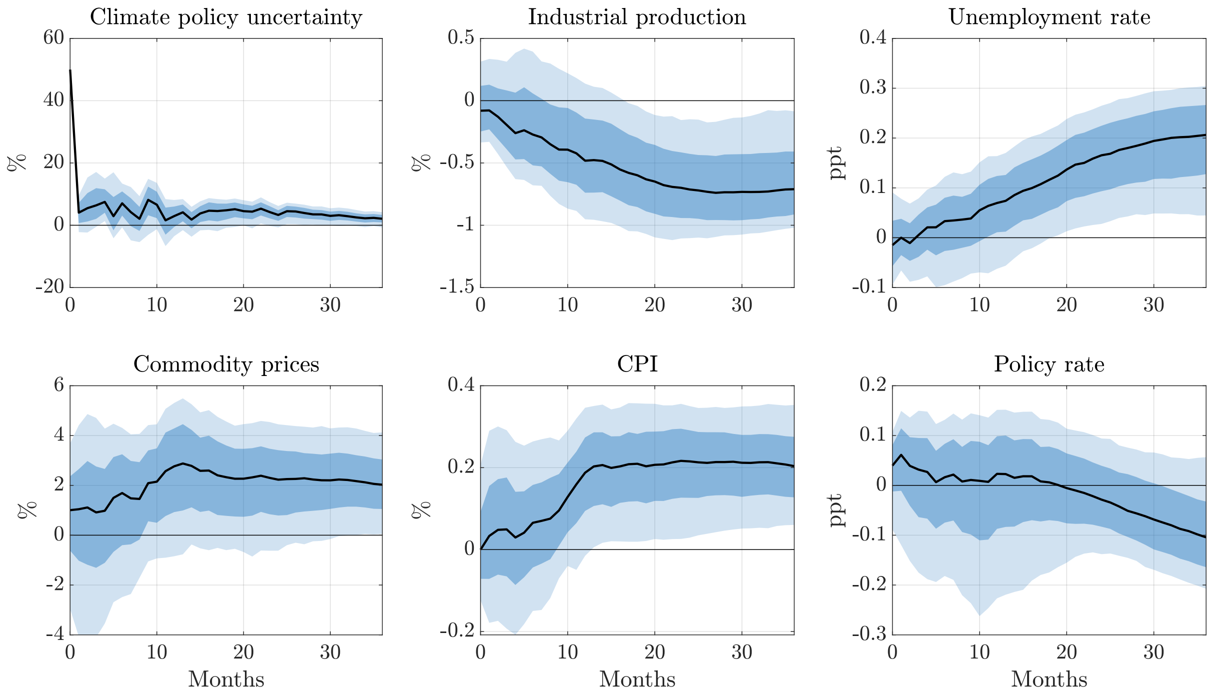
How does climate policy uncertainty affect the macroeconomy? In this section, we present the results based on our VAR model for the United States.

Macroeconomic effects. Figure 4 shows the impulse responses to a climate policy uncertainty shock, estimated based on the external instruments VAR approach. Because our uncertainty index has arbitrary scale, we normalize the shock to a 50 percent increase in climate policy uncertainty, approximately a one-standard-deviation shock. This magnitude corresponds roughly to the increase in climate policy uncertainty observed over the 2016–2020 election cycle.

The heteroskedaticity-robust first-stage F-statistic is 23.54 and thus safely above the commonly used threshold of 10. We thus proceed with conducting standard inference. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

A climate policy uncertainty shock leads to a short-lived increase in the CPU index, consistent with the transient nature of newspaper reporting. The underlying increase in climate policy uncertainty, however, has substantial implications for the U.S. economy. Industrial production declines, reaching a trough of approximately -0.7 percent after two years, while the unemployment rate increases by 0.2 percentage points. These responses are statistically significant at the 90 percent confidence level, especially at longer horizons. The shock also leads to an increase in prices: commodity prices increase contemporaneously, reaching a peak of 2.9 percent, while headline consumer prices rise by around 0.2

Figure 4: Impulse responses to a climate policy uncertainty shock



First-stage regression: F-statistic: 23.54, R^2: 2.81%

Notes: Impulse responses to a climate policy uncertainty shock, normalized to increase the CPU index by 50 percent on impact, estimated using an external instruments VAR (3) with the event-based climate policy uncertainty series as an instrument. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

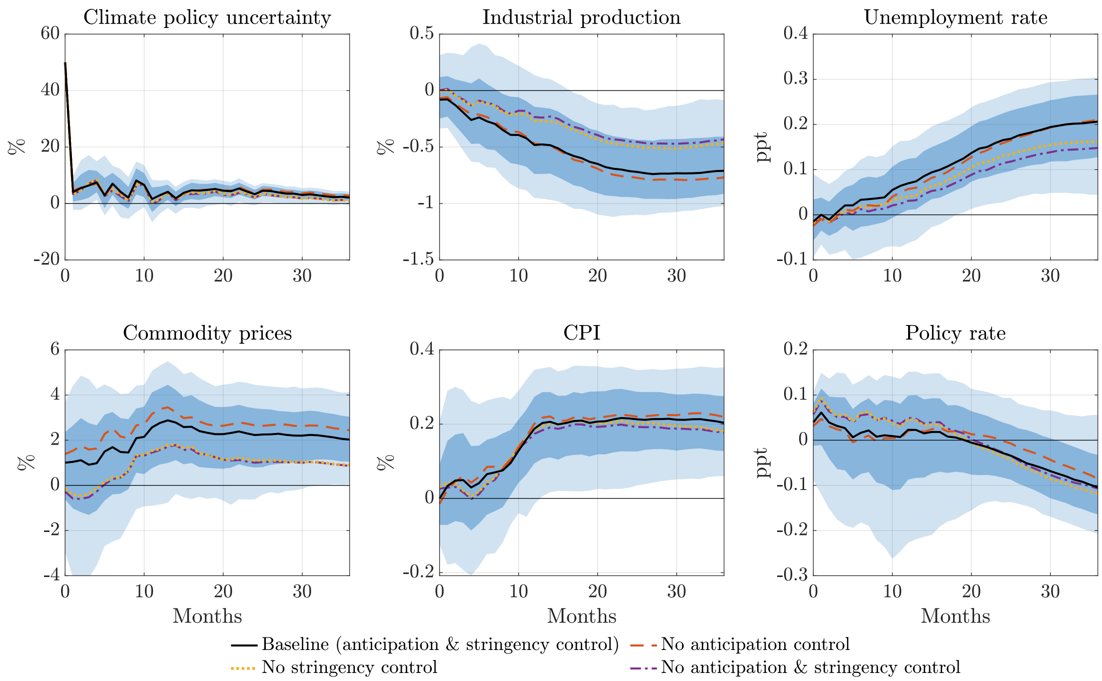
percent. The divergence between prices and activity creates a trade-off for monetary policy; in the short term, monetary policy tends to lean against the inflationary pressures, while in in the longer term, it accommodates the fall in economic activity. The estimated response, however, is imprecise and not statistically significant at the 90 percent level.

Controlling for news and other uncertainty. We now discuss the role of controlling for policy stringency in the instrument construction, as well as the robustness of the resulting impulse responses to additional policy news and uncertainty controls.

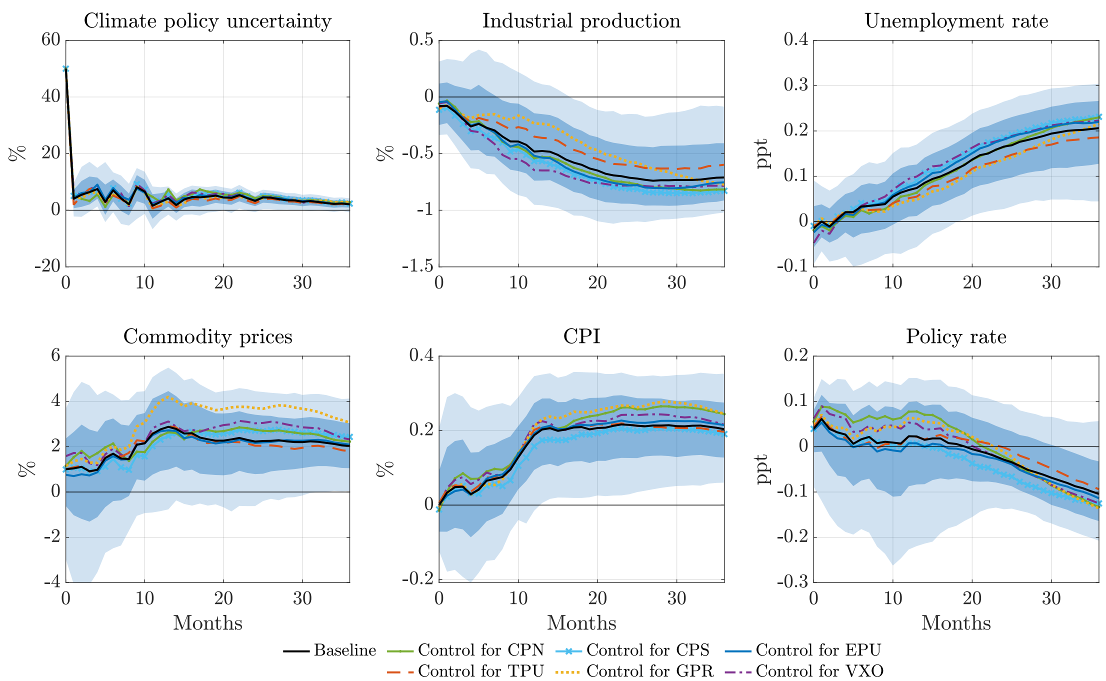
Figure 5a assesses the impact of controlling for anticipation and policy stringency in the construction of our instrument. We compare our baseline responses to versions of the instrument that omit either the anticipation adjustment or the stringency control. Removing the anticipation adjustment has little effect on the estimated responses, indicating that anticipation plays a negligible role in our context. By contrast, failing to purge the instrument of the first-moment component materially alters the responses: the effects on industrial production, unemployment, and commodity prices are noticeably attenuated

Figure 5: The role of controlling for news and other uncertainty

(a) Anticipation and policy stringency controls in instrument construction



(b) Aggregate news and other uncertainty controls



Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR (3). Panel (a) compares responses using our baseline instrument (black) to ones where we exclude controls for anticipation and stringency. Panel (b) compares our baseline response (black) to the responses from models where we control for climate policy news (green), climate policy sentiment (cyan), economic policy uncertainty (blue), trade policy uncertainty (orange), geopolitical risk (yellow), and the VXO (purple). The lines are point estimates, and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

when policy stringency is not controlled for. This pattern is consistent with directional policy news contaminating the instrument when first-moment effects are not removed.

At the same time, the precise way in which policy stringency is measured is of second-order importance. Whether stringency is captured purely by the direction of the policy change or augmented with measures of the magnitude of the action—such as whether it is legally binding or scaled by reporting intensity—yields very similar impulse responses, see Appendix Figure D.3. This indicates that what matters for identification is purging the directional component of policy news, rather than the exact parametrization of stringency.

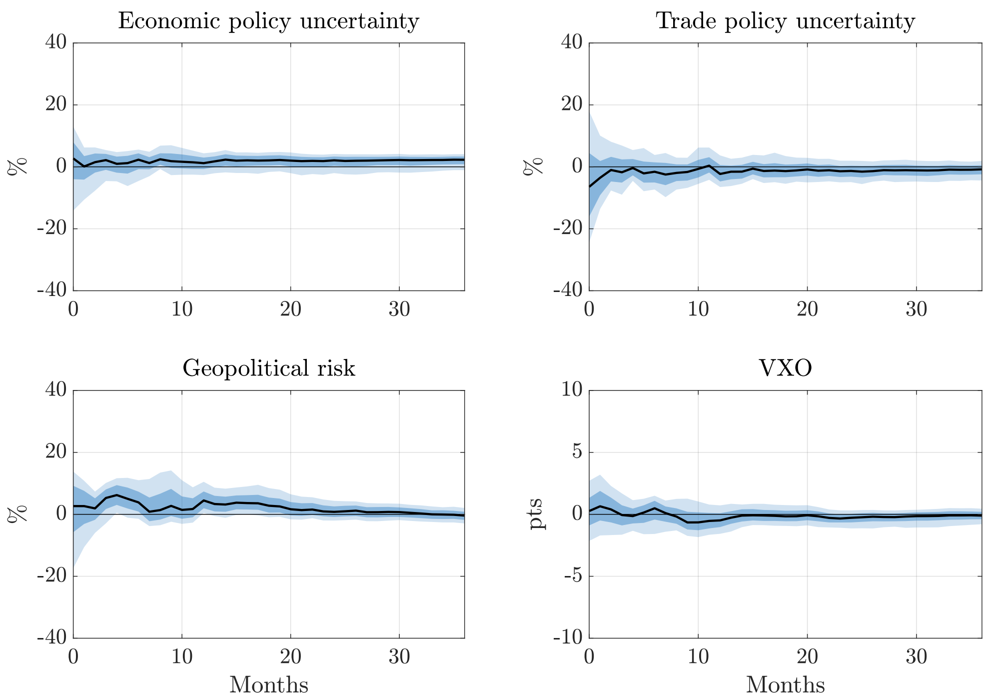
Figure 5b assesses the robustness of our baseline results to controlling for policy news and other sources of uncertainty in our VAR model. First, the estimated responses are virtually unchanged when we control for a climate policy news index or an aggregate climate policy sentiment index in the spirit of Hassan et al. (2019) (see Appendix A.3 for details on the construction of these indices). Second, our results are robust to controlling for the Baker, Bloom, and Davis (2016) economic policy uncertainty index, indicating that our instrument successfully isolates climate-specific uncertainty from broader economic and political developments. Finally, the results are unaffected by controls for trade policy uncertainty, geopolitical risk, or financial market volatility.

Finally, we present results from a model identified using short-run timing restrictions, as commonly employed in the policy uncertainty literature. Appendix Figure D.18 shows that identifying a shock to the climate policy uncertainty index under this identification scheme yields responses that are similar to those obtained using our baseline external-instruments VAR. Since the instrumental-variable approach relies on weaker and more transparent identifying assumptions, this close correspondence lends credibility to the timing-restriction approach in this context. As expected, the recursive VAR delivers tighter confidence bands given the stronger identifying assumptions.

Effects on other uncertainty measures. To sharpen the interpretation of the shock, we study how climate policy uncertainty influences a wide range of other uncertainty measures. To this end, we employ the marginal VAR approach, augmenting the baseline VAR by one variable at a time as in Gertler and Karadi (2015). The results are shown in Figure 6. Climate policy uncertainty shocks have no meaningful impact on other policy uncertainty and risk measures. In the top panel, we observe that the response of economic and trade policy uncertainty remain close to zero and are statistically insignificant. Similarly, in the bottom panel, we see no evidence of an increase in geopolitical risk or financial uncertainty—as measured by the VXO—following the shock.

These findings suggest that the identified shock represents a distinct source of policy

Figure 6: Impact on other uncertainty and risk measures



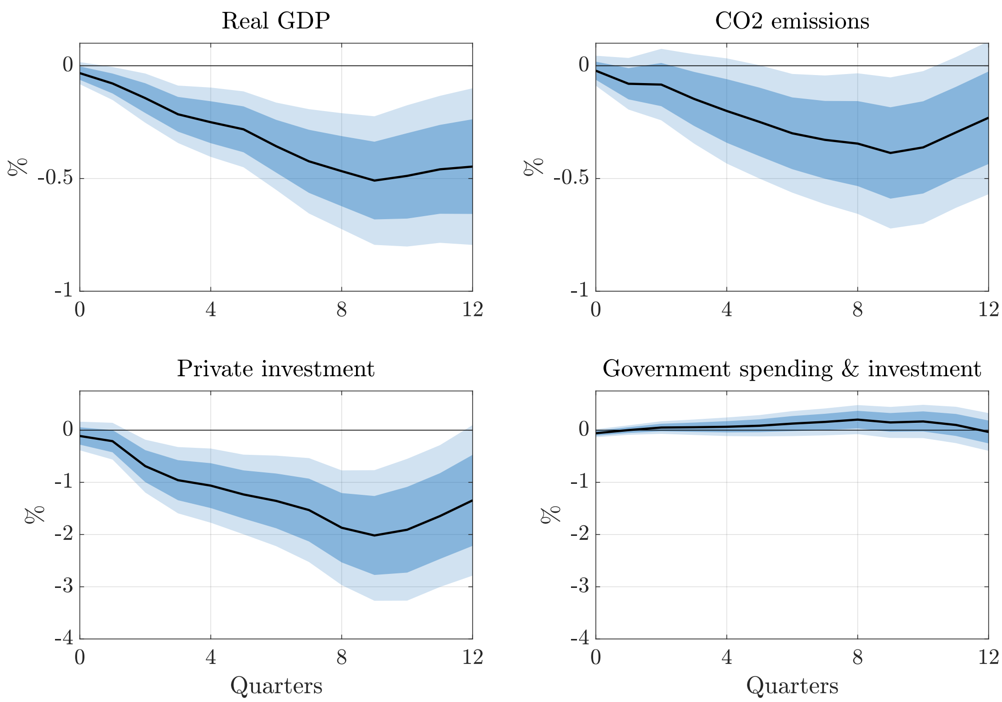
Notes: Impulse responses of uncertainty and risk measures to a climate policy uncertainty shock, estimated by augmenting our baseline external instruments VAR (3) with one uncertainty measure at a time. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

uncertainty specific to climate policy, reinforcing the validity of our identification strategy.

Broader impacts. To obtain a better understanding of how climate policy uncertainty shocks transmit to the macroeconomy, we study the effects on a selection of macroeconomic variables, including GDP, emissions, and investment. These variables are only available at the quarterly frequency, where our external instruments approach does not work very well due to power problems (Nakamura and Steinsson, 2018). Therefore, we estimate these responses using local projections on the aggregated climate policy uncertainty shock from the VAR, as explained in Section 3.2. As controls, we include four lags of the dependent variable, four lags of the shock, and a linear time trend.

Figure 7 presents the results. The top panel shows the GDP and emissions responses. Climate policy uncertainty shocks have broad-based economic effects: real GDP falls significantly with a lag, reaching a trough of about -0.5 percent, with dynamics similar to industrial production. CO_2 emissions also decline significantly, but largely in line with the fall in activity; if anything, the emissions intensity increases slightly (see Appendix Figure D.19). This pattern is consistent with Fried, Novan, and Peterman (2021). While emissions fall, the reduction comes at a substantial economic cost. Indeed, existing empirical estimates suggest that instruments such as carbon taxes or cap-and-trade systems can achieve comparable emissions reductions at much lower cost (see e.g. Känzig, 2025; Metcalf and Stock, 2023).

Figure 7: Impacts on GDP, emissions, and investment



Notes: Impulse responses of GDP, emissions, and investment to a climate policy uncertainty shock, estimated using local projections (7) on the aggregated climate policy uncertainty shock extracted from our baseline external instruments VAR. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

The observed fall in emissions is inconsistent with the green paradox (see e.g. Sinn, 2008). According to this literature, uncertainty about future climate policy should increase current emissions by encouraging fossil fuel producers to front-load extraction in anticipation of tighter regulation. In contrast, our results suggest that the economic consequences associated with climate policy uncertainty are severe enough to weigh down on emissions.

The bottom panel shows the responses of private investment as well as government spending and investment. The shock leads to a substantial decline in private investment. After two years, private investment falls by around 2 percent. This is consistent with theories that emphasize uncertainty as a drag on investment, for instance through real options or cost-of-capital effects (Bloom, 2009; Baker, Bloom, and Davis, 2016). Interestingly, climate policy uncertainty has no significant impact on government spending and investment, as the response remains close to zero and statistically insignificant. This pattern is consistent with an uncertainty shock, providing further support for our identification strategy. By contrast, a first-moment policy shock would be expected to induce a significant response in public investment.

4.1. Climate vs. economic policy uncertainty

We have seen that climate policy uncertainty shocks have substantial macroeconomic consequences. This aligns with a well-established literature highlighting uncertainty and risk as important drivers of economic fluctuations (Bloom, 2014). However, what do we learn from studying the effects of climate policy uncertainty specifically? Does climate policy uncertainty affect the economy differently from other dimensions of policy uncertainty?

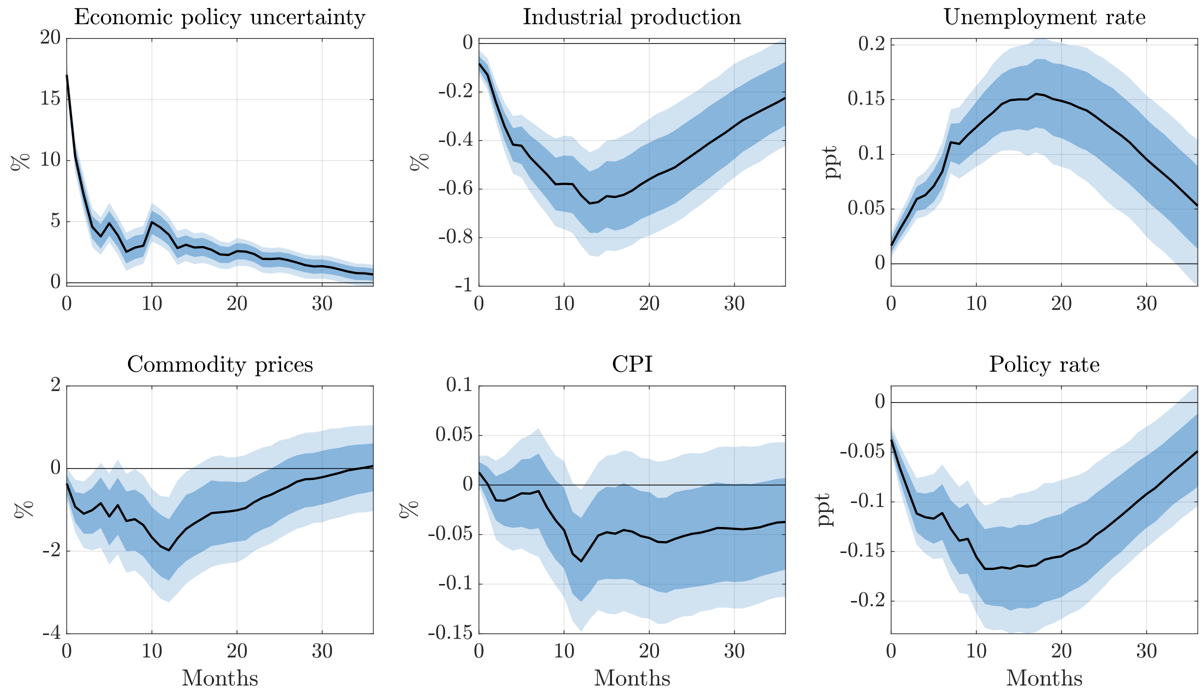
To answer this question, we revisit the macroeconomic effects of economic policy uncertainty (EPU). We use the index of Baker, Bloom, and Davis (2016) in our VAR model and identify an economic policy uncertainty shock using short-run zero restrictions. Specifically, we assume that economic policy uncertainty is affected by macroeconomic variables only with a lag.

Figure 8 presents the results. Following a one-standard deviation shock, economic policy uncertainty increases sharply and remains elevated for about two years. This has significant macroeconomic consequences. Industrial production falls, reaching a trough at about -0.7 percent, while the unemployment rate increases by around 0.15 percentage points. These effects on economic activity are comparable to the impacts of climate policy uncertainty, albeit somewhat less persistent.

The price responses differ fundamentally between the two shocks. While climate policy uncertainty leads to an *increase* in commodity and consumer prices, economic policy uncertainty leads to a *fall* in both prices. Thus, economic policy uncertainty shocks appear to transmit primarily as aggregate demand shocks, as in Leduc and Liu (2016), while climate policy uncertainty shocks seem to transmit more like supply shocks. Consistent with this evidence, the monetary policy response also differs across the two shocks. After an economic policy uncertainty shock, the central bank responds by substantially easing policy rates to counteract the sharp drop in demand. This contrasts sharply with the slightly positive interest rate response we estimate after a climate policy uncertainty shock, at least in the short term.

Why do climate policy uncertainty shocks tend to increase prices while broader economic policy uncertainty shocks lower them? In theory, the price response to uncertainty shocks is ambiguous and depends on the strength of the underlying transmission chan-

Figure 8: Impulse responses to an economic policy uncertainty shock



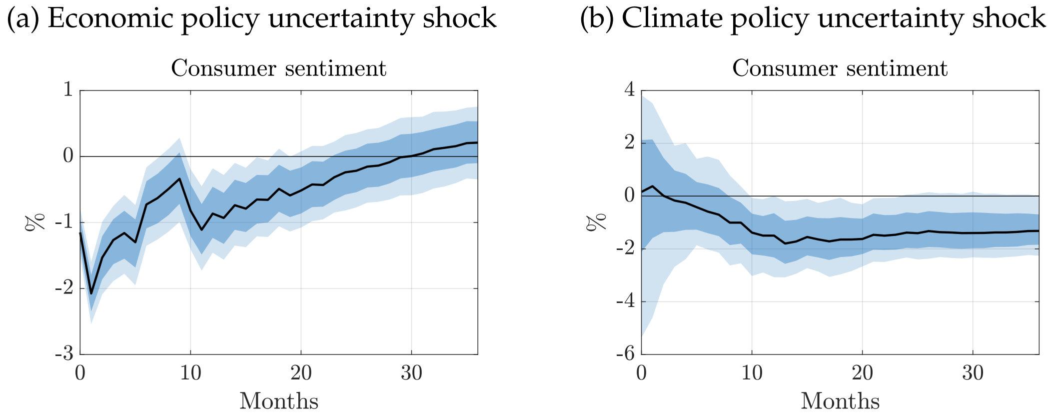
Notes: Impulse responses to a one standard deviation economic policy uncertainty shock, estimated using a VAR identified with short-run zero restrictions. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

nels. The literature focuses on three main channels. First, the precautionary demand channel (Leduc and Liu, 2016; Basu and Bundick, 2017): higher uncertainty leads agents to cut spending and engage in precautionary saving, which reduces aggregate demand and puts downward pressure on prices. Second, the real options channel (see e.g. Dixit and Pindyck, 1994; Bloom, 2009): after a rise in uncertainty, firms delay their investment and hiring. Third, the precautionary pricing channel (Born and Pfeifer, 2014; Ilut and Schneider, 2014; Fernández-Villaverde et al., 2015): increased uncertainty raises the potential for higher future costs, leading firms to raise prices preemptively. Thus, the price response will depend on the relative strength of demand- and supply-side adjustments.

Our results suggest that climate policy uncertainty shocks mainly transmit through supply-side channels. We confirm this notion by looking at the effects of consumer sentiment as a proxy for demand pressures. To estimate these responses, we augment our VAR models with the index of consumer sentiment from the Michigan survey.

Figure 9 shows that economic policy uncertainty leads to a significant decline in consumer sentiment. This is consistent with the notion that consumer confidence is an important propagation channel of economic policy uncertainty shocks, leading to weaker

Figure 9: Impacts on consumer sentiment



Notes: Impulse responses of consumer sentiment. Panel (a) shows the responses to an economic policy uncertainty shock, estimated using the recursive VAR augmented with the consumer sentiment measure. Panel (b) shows the responses to a climate policy uncertainty shock, estimated using the external instruments VAR (3) augmented with the consumer sentiment measure. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

demand for goods and services. This reduced demand may in turn further discourage firms from investing, either due to lower anticipated returns or financial constraints. In contrast, climate policy uncertainty shocks have a muted impact on consumer sentiment. This suggests that climate policy uncertainty propagates primarily through supply-side channels, at least initially.

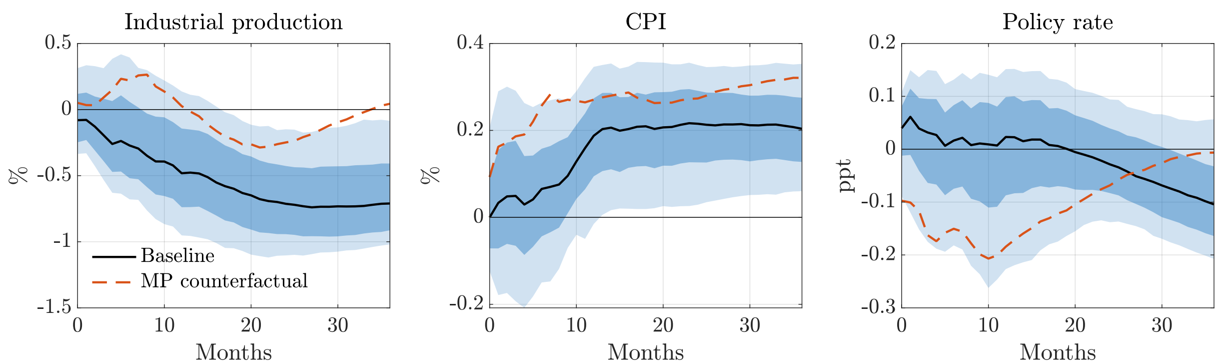
4.2. The role of monetary policy

Climate policy uncertainty creates a trade-off for monetary policy: economic activity falls while consumer prices rise. Our results point to a largely insignificant monetary policy response. This contrasts starkly to how monetary policy responds to other uncertainty shocks, which tend to propagate more like demand shocks and are accommodated by the monetary authority.

How important is the monetary policy response for the transmission of climate policy uncertainty shocks? To answer this question, we perform a monetary policy counterfactual exercise, relying on the approach by McKay and Wolf (2023). The idea is to leverage estimated impulse responses to monetary policy shocks to impose a counterfactual monetary response to climate policy uncertainty shocks. By only using a combination of contemporaneous monetary policy shocks, the contemplated counterfactual policy is incorporated in private-sector expectations ex-ante and thus robust to the Lucas critique.

We are interested in how the impacts of climate policy uncertainty shocks differ in a scenario where monetary policy accommodates these shocks in the same way as broader economic policy uncertainty shocks.[7] To condition the response, we identify a monetary policy shock using high-frequency surprises around FOMC announcements from Bauer and Swanson (2023), purged from relevant macroeconomic and financial data predating the announcement.[8]

Figure 10: Monetary policy counterfactual



Notes: Impulse responses to a climate policy uncertainty shock using our baseline model (black) and under a counterfactual monetary policy rule (dashed red) that imposes the same monetary response as to economic policy uncertainty shocks. The lines are point estimates and the dark and light blue shaded areas are 68 and 90 percent confidence bands of our baseline model.

Figure 10 shows the responses to a climate policy uncertainty shock under the counterfactual monetary policy response. By accommodating the climate policy uncertainty shock, monetary policy is able to largely stabilize the industrial production response. This comes at the cost of higher inflation, however the CPI stabilizes at a level that is only moderately higher than in the baseline case. This suggests that there may be a trade-off that monetary policymakers could exploit, even though the optimal monetary policy response will, of course, depend on the policymaker's loss function.

Overall, these results highlight the important role of monetary policy in shaping the transmission of climate policy uncertainty shocks and point to the need for coordination between fiscal and monetary policy. Clear and predictable climate policy, supported by an appropriate monetary response, is key to mitigating the economic costs of uncertainty while advancing long-term sustainability goals.

[7] To make the shocks more comparable, we use an EPU shock that has comparable macroeconomic consequences to a CPU shock, as measured by the cumulative response of industrial production.

[8] It turns out that a single monetary shock is sufficient to approximate our counterfactual policy response reasonably well. However, as a robustness check, we also employ two types of monetary policy shocks, adding a shock identified using the high-frequency instrument from Miranda-Agrippino and Ricco (2021b). The results turn out to be very similar.

4.3. Sensitivity

In this section, we perform a comprehensive series of sensitivity checks on our approach to measurement, the identification strategy, as well as the empirical specification.

Measurement of climate policy uncertainty. Given the challenges in measuring climate policy uncertainty, we assess the sensitivity of our results with respect to measurement choices. Appendix Figure D.9 shows the responses using a broader CPU index—based on slightly less restrictive dictionary criteria—and the original index in Gavriilidis (2021), which relies on an even less specific set of keywords. The results are robust to using these alternative climate policy uncertainty indices. This illustrates the advantage of our external instruments approach, leveraging information specific to major climate policy uncertainty events.

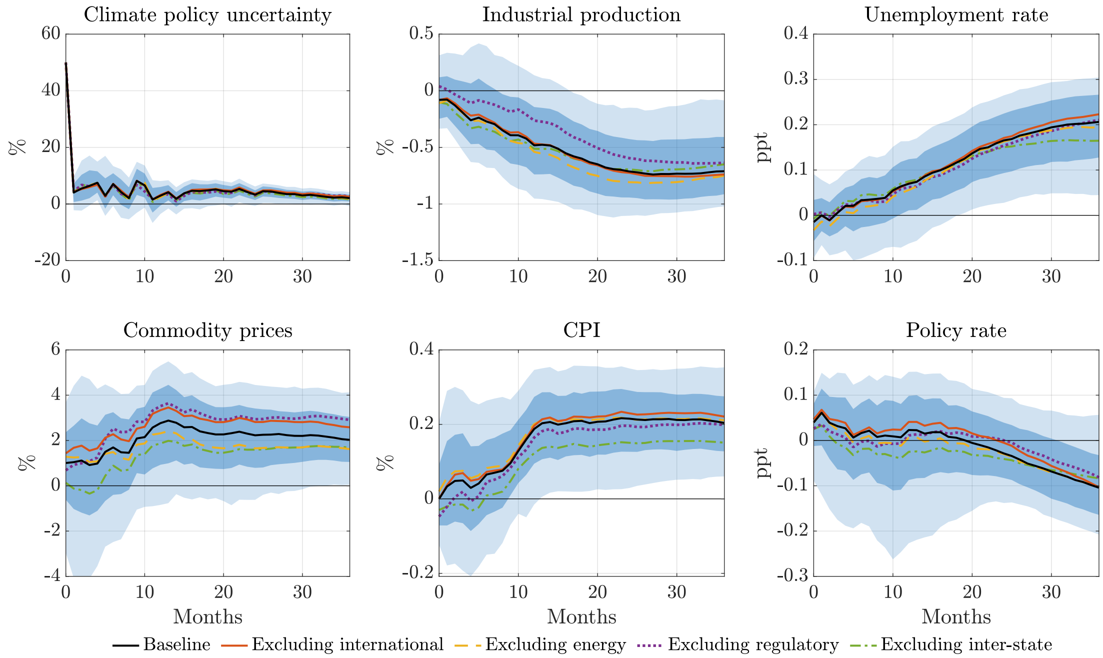
Event selection. Next, we assess the sensitivity of our results to the selection of events used to construct the instrument. While our baseline adopts an agnostic approach that includes all events identified through the narrative analysis (Section 3.1), we examine robustness to excluding specific subsets of events, such as international agreements or inter-state developments, which may be less directly tied to national climate policy, and energy policy or regulatory actions, which could reflect broader economic policy uncertainty. As shown in Figure 11a, the results are not driven by any particular subset of events. A complementary jackknife exercise further confirms that no single event disproportionately influences the estimates (Appendix Figure D.2).

Additional controls. We also assess robustness to a range of additional controls that address potential confounding channels. First, climate policy reporting may rise mechanically following major natural disasters or extreme temperature realizations. In this case, our instrument could partly reflect physical climate shocks rather than policy uncertainty. We therefore control for physical climate risk, proxied by both the number of natural disasters and global temperature anomalies, with virtually no effect on the results (Appendix Figure D.11).

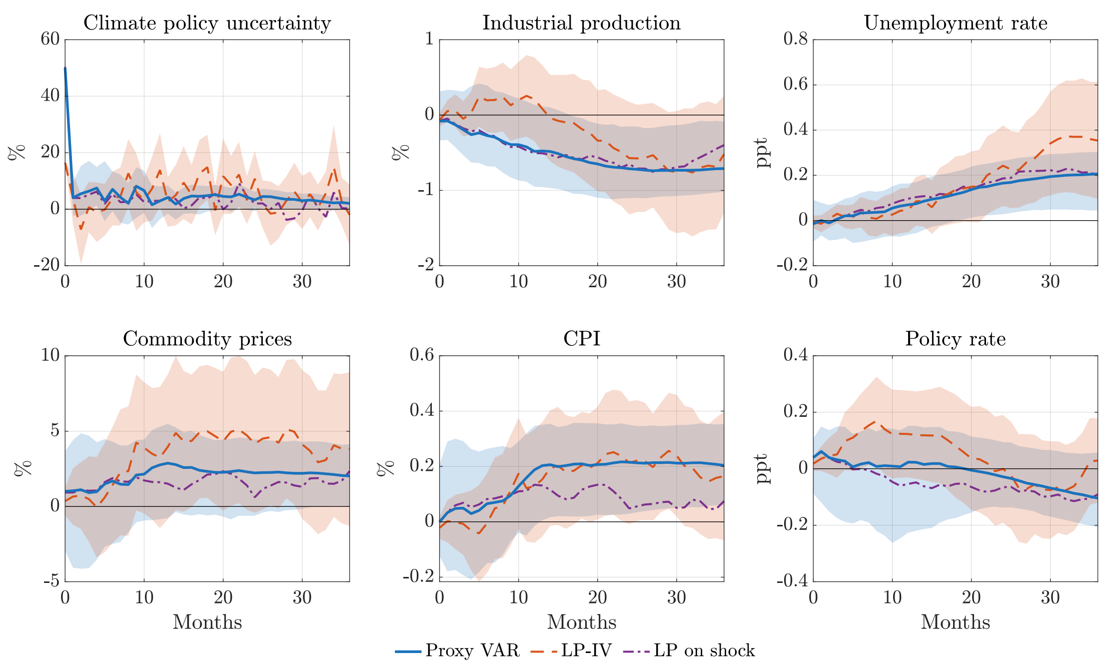
Second, climate policy is highly partisan, and shifts in political control may be correlated with a wide range of other policy changes, including fiscal and regulatory interventions. To address this concern, we control for partisan conflict and changes in federal administrations. To control for countercyclical green fiscal policy episodes specifically, such as those associated with the American Recovery and Reinvestment Act (Popp et al., 2021),

Figure 11: Sensitivity analysis

(a) Event selection



(b) Estimation approach



Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR (3). Panel (a) compares responses using our baseline instrument (black) to ones where we exclude specific subsets of events. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model. Panel (b) compares responses estimated using our baseline external instruments VAR (blue) to the LP on the VAR shock measure (7) in purple and the LP-IV specification (8) in orange. The lines are the point estimates and the blue and orange shaded areas are 90 percent confidence bands for the external instruments VAR and the LP-IV, respectively.

we further include government spending interacted with a Democratic-administration indicator. As shown in Appendix Figure D.10, the estimated responses are essentially unchanged.

VAR assumptions. As discussed in Section 3.2, the external instruments VAR approach relies on some potentially restrictive assumptions, in particular invertibility and no lag truncation bias. To assess how restrictive these assumptions are, we estimate the effects of climate policy uncertainty shocks using local projections.

To assess the extent of lag truncation bias, we estimate the responses using simple local projections on the identified VAR shock. This relaxes the dynamic VAR structure but still retains the invertibility assumption. From Figure 11b, we can see that the responses are very similar to our baseline responses, suggesting that our dynamic VAR structure is flexible enough to capture the U.S. macroeconomic dynamics adequately. In Appendix D.2, we further show that our results are robust to varying the lag order of our VAR model. Finally, we also report results from a local projections–instrumental variables specification, which does not rely on invertibility. The responses are broadly similar to those from our baseline VAR, with industrial production adjusting somewhat more slowly, though all responses are less precisely estimated.[9]

Sample and specification choices. Finally, we study the sensitivity of our results with respect to some additional modeling choices. Specifically, the results turn out to be robust to omitting the deterministic time trend or controlling for the global financial crisis using a dummy variable. Our results are also robust to extending the sample until 2024. See Appendix D.2 for more details.

5. Firm-level and sectoral impacts

We have established that climate policy uncertainty has significant macroeconomic consequences. We now examine the effects at the firm level for three reasons. First, to assess whether firms perceive climate policy uncertainty as a material source of financial risk, providing a microeconomic foundation for the aggregate effects we document. Second, to uncover underlying heterogeneity in responses that is masked in aggregate data. Third, focusing on within-firm variation allows us to better control for confounding factors.

[9] To make the methods more comparable, we rescale the instrumental variable in the local projections–instrumental variable specification such that the cumulative response of climate policy uncertainty is comparable to that under the VAR specification.

Data. To assess the impact of climate policy uncertainty at the firm level, we rely on the quarterly Compustat Fundamentals dataset, which includes standardized financial data for all public companies. We complement this dataset with the annual Compustat Fundamentals, as some variables, such as employment, are unavailable at the quarterly level. To gauge firms' exposure to climate change, we use the climate change exposure dataset by Sautner et al. (2023), which provides quarterly, firm-level exposure measures derived from earnings conference call transcripts. For additional details on the data and relevant variables, see Appendix C.2.

5.1. Average effects of climate policy uncertainty

We begin by analyzing how firm-level variables respond, on average, to a climate policy uncertainty shock. To estimate the dynamic causal effects of a climate policy uncertainty shock in the panel, we use the panel local projections approach (Jordà, Schularick, and Taylor, 2015). This method allows us to estimate the average effect of a climate policy uncertainty shock across firms, controlling for time-invariant firm characteristics. Specifically, we estimate the following series of panel regressions for each horizon h:

$$y_{j,t+h} = \alpha_{j,h} + \theta_h \varepsilon_{1,t} + \boldsymbol{\beta}_h' \mathbf{x}_{j,t-1} + \nu_{j,t+h}, \tag{10}$$

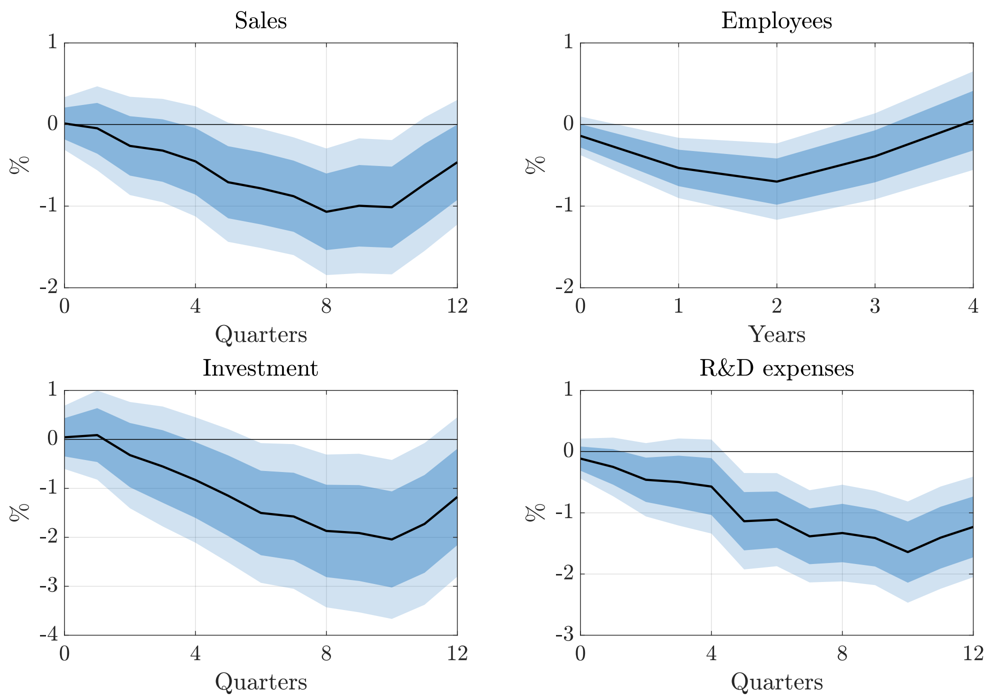
where, $y_{j,t}$ is the (log) outcome variable of interest for firm j at time t, $\alpha_{j,h}$ is a firm fixed effect, $\varepsilon_{1,t}$ is the climate policy uncertainty shock, θ_h is the dynamic causal effect of interest at horizon h, $\mathbf{x}_{j,t-1}$ is a vector of lagged controls, and $\nu_{j,t}$ is an error term. Our main outcome variables of interest are available at the quarterly frequency.[10] For the variables only available at the annual frequency, we aggregate the monthly climate policy uncertainty shock from the VAR before implementing the local projections, as detailed in Section 3.2.

For the quarterly specification, we include four lags of the dependent variable, four lags of the shock, and a linear time trend as controls, consistent with our baseline specification for aggregate variables. We also include quarter fixed effects to account for seasonality in the outcome variable, though the results remain robust to excluding them. For the annual specification, we similarly include one lag of the dependent variable, one lag of the shock, and a linear trend as controls.

Our main outcome variables of interest are firm-level sales, employees, investment, and R&D expenses. Our sample is an unbalanced panel from 1986 to 2019 (136 quarters)

[10] To economize on notation, we omit the index of the outcome variable i that we are interested in.

Figure 12: Average effect of climate policy uncertainty shock



Notes: Average response of firm-level variables to a climate policy uncertainty shock, estimated using panel local projections (10) on the aggregated climate policy uncertainty shock, extracted from our baseline external instruments VAR. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

with 11,871 firms, which, net of missing data, amounts to 644,166 firm-quarter observations. For inference, we use heteroskedasticity-robust standard errors clustered at the time level following Almuzara and Sancibrián (2024).

Figure 12 shows the impulse responses of firm-level variables to a climate policy uncertainty shock, estimated in the panel. The top panel presents the sales and employment responses. Average firm-level sales decline, reaching a trough of -1 percent after two years, consistent with the fall in industrial production and real GDP observed in the aggregate. Average employment also falls by 0.7 percent over the same period, inversely mirroring the increase in unemployment in the VAR.

The bottom panel presents the responses of investment and R&D expenses. Average firm-level investment declines substantially by 2 percent after two years, consistent with the response of aggregate private investment. Finally, R&D expenses also decline significantly by 1.6 percent.

Overall, these results point to substantial impacts of climate policy uncertainty at the firm level, indicating that firms perceive it as a material source of financial risk. Reassuringly, the average firm-level responses are broadly comparable to the aggregate effects we estimate at the macro level.

5.2. Heterogeneous effects of climate policy uncertainty

The average effect may mask substantial heterogeneity in firms' responses to climate policy uncertainty. For example, does a firm's prior exposure to climate change influence its response to climate policy uncertainty? Do firms with different characteristics, such as industry sector, exhibit enduring differences in their response to the shock? In this section, we explore these potential sources of heterogeneity in greater detail.

Heterogeneous effects based on exposure to climate change. We first examine how a firm's exposure to climate change influences its response to climate policy uncertainty. A challenge is that firms may differ in their average exposure due to unobserved characteristics. To address this, we will exploit the variation in firms' exposure to climate change over time. By leveraging within-firm variation, we can better control for these unobserved characteristics.

To measure a firm's exposure at a given point in time, we use the firm-level climate change exposure measures from Sautner et al. (2023), which capture the relative frequency of climate-related bigrams in earnings conference call transcripts. Our sample includes 4,164 firms from 2001 to 2019 (76 quarters), yielding 135,957 observations after accounting for missing data.

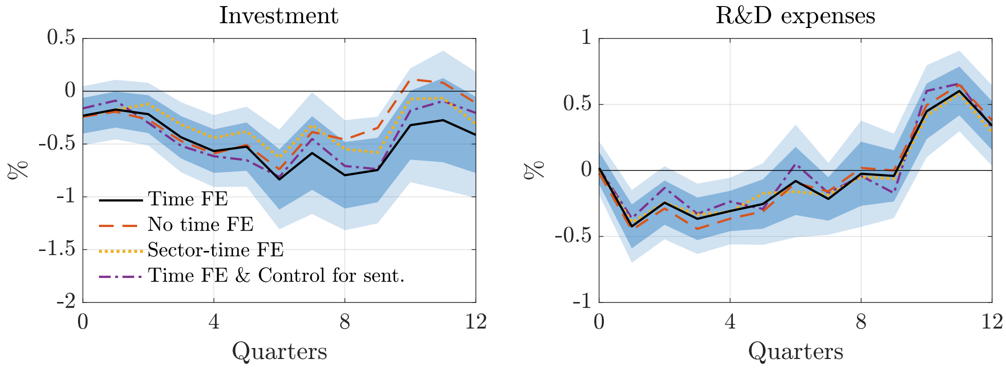
To analyze how a firm's response to climate policy uncertainty varies with its climate change exposure, we interact the climate policy uncertainty shock with the firm's pre-shock exposure relative to its average exposure:

$$y_{j,t+h} = \alpha_{j,h} + \delta_t + \gamma_h(\text{Exp}_{j,t-1} - \overline{\text{Exp}_j}) \times \varepsilon_{1,t} + \boldsymbol{\beta}_h' \mathbf{x}_{j,t-1} + \nu_{j,t+h}, \tag{11}$$

where, $y_{j,t}$ is the (log) outcome variable of interest for firm j at time t, $\text{Exp}_{j,t-1}$ is the climate change exposure measure for firm j at time $t-1$, $\overline{\text{Exp}_j}$ is the average exposure of firm j over the sample, $\varepsilon_{1,t}$ is the climate policy uncertainty shock, and γ_h is the dynamic causal effect of interest at horizon h. $\alpha_{j,h}$ is a firm fixed effect, δ_t is a time fixed effect, $\mathbf{x}_{j,t-1}$ is a vector of lagged controls and $\nu_{j,t}$ is an error term. The specification is similar to the one used in Ottonello and Winberry (2020).

Importantly, this specification allows us to control for many unobserved confounding factors using fixed effects. In our main specification we include time fixed effects. As an alternative, we also report results from a specification that controls for the climate pol-

Figure 13: Heterogeneous effects based on prior exposure to climate change



Notes: Heterogeneous response of investment and R&D expenses to a climate policy uncertainty shock, estimated using panel local projections (11) on the aggregated climate policy uncertainty shock interacted with firm-level climate change exposure. The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for the model with time fixed effects.

icy uncertainty shock instead of the time fixed effects, as in (10). Our most restrictive specification includes sector-by-time fixed effects, controlling for common, sector-specific trends. We also consider a specification where we control for the firm-level climate sentiment measure by Sautner et al. (2023) to further alleviate concerns about first-moment impacts.

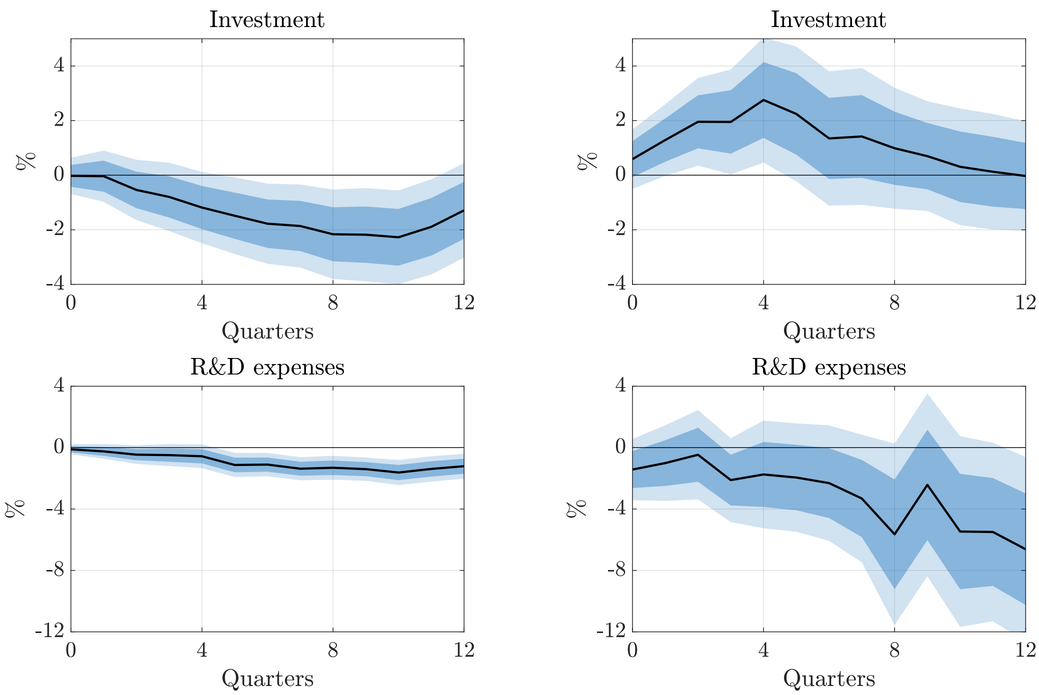
The coefficient γ_h captures how a firm's response to a climate policy uncertainty shock depends on its climate change exposure prior to the shock. By leveraging within-firm variation in exposure, we ensure that our results reflect how an individual firm responds when its exposure is above or below its average level, rather than being driven by permanent differences across firms. To facilitate interpretability, we standardize the relative exposure measure over the entire sample.

Consistent with our baseline panel local projections specification, we control for four lags of the dependent variable, four lags of the shock, four lags of the shock interacted with the exposure measure, and the relative level of climate change exposure. In the specifications without time fixed effects, we additionally control for a linear trend and quarter fixed effects.

Figure 13 shows how the response of investment and R&D expenses to a climate policy uncertainty shock varies with a firm's climate change exposure. A one-standard-deviation increase in a firm's relative exposure leads to an additional 0.8 percent decline in investment after two years and an additional 0.3 percent reduction in R&D expenses after one year. Thus, firms experience sharper short-term declines in investment and R&D expenses when their exposure to climate change is higher. Interestingly, the same firms eventually end up increasing their R&D expenses after three years, suggestive of strate-

Figure 14: Heterogeneous effects based on sector

(a) All sectors (excl. oil, gas, and utilities)　　(b) Oil, gas, and utilities



Notes: Heterogeneous response of investment and R&D expenses to a climate policy uncertainty shock by sector, estimated using sector-specific panel local projections (10) on the aggregated climate policy uncertainty shock. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

gic efforts to adapt to or mitigiate climate policy uncertainty. Our findings remain robust when we exclude time fixed effects, include the more stringent sector-by-time fixed effects, or control for firm-level climate sentiment.

Sectoral heterogeneity. We now explore how firms' response to climate policy uncertainty differs across sectors, an important dimension of permanent heterogeneity. Not all sectors are equally exposed to climate policy. In principle, some sectors may even benefit from higher climate policy uncertainty. To analyze this, we estimate the panel local projection specification (10) separately for different sectors. In particular, we separate the mining, quarrying, oil and gas extraction, and utilities sector—which may be especially affected by climate policy uncertainty—from all other sectors.

Figure 14 presents the average response of investment and R&D expenses to a climate policy uncertainty shock across the two sector groups. Most sectors experience significant declines in both investment and R&D, with responses close to the overall average (see Appendix Figure D.20); these sectors are therefore grouped in Panel (a). In contrast, the mining, quarrying, oil and gas extraction, and utilities sectors in Panel (b) exhibit an increase in investment alongside a pronounced fall in R&D. This suggests that climate policy uncertainty drives higher investment in fossil fuel-related sectors, potentially reflecting the acceleration of brown projects ahead of stricter regulation, while reducing longer-term R&D expenses that may support the green transition. This interpretation aligns with Noailly, Nowzohour, and Van Den Heuvel (2022), which finds that environmental policy uncertainty lowers venture capital funding for the low-carbon economy.

Overall, these findings are consistent with a green paradox at the micro level, in which uncertainty about future climate policy strengthens incentives to extract fossil fuels. They also highlight how such uncertainty can exacerbate transition costs through misallocative forces.

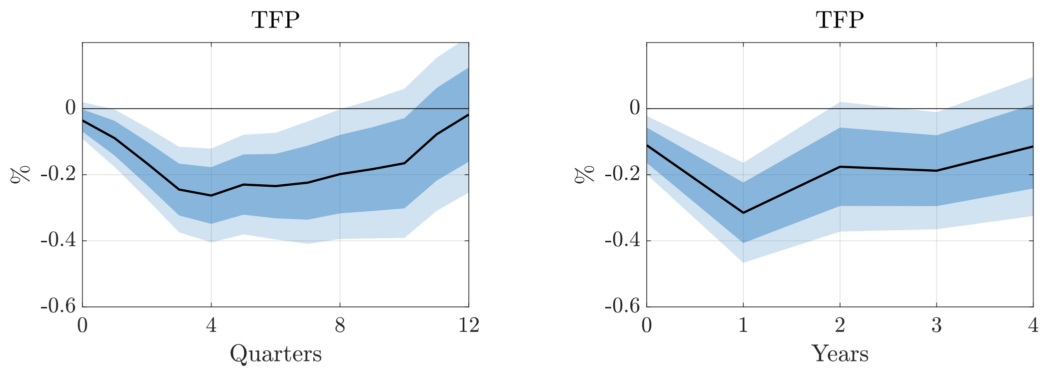
5.3. Longer-term impacts

We have shown that climate policy uncertainty is associated with a pronounced decline in investment and R&D, with potentially important longer-run implications for productivity. Faced with uncertain regulatory environments, firms may delay or scale back innovative investment, including in sectors not directly targeted by climate policy. Such responses can slow technological progress and weigh on productivity growth. In addition, policy uncertainty may distort resource allocation by encouraging investment in firms with high current returns but uncertain long-term viability—particularly in carbon-intensive sectors whose markets are likely to shrink as climate policies tighten in the future. This can crowd out investment in more innovative or lower-emission firms that are better positioned for long-run growth, further depressing aggregate productivity. Consistent with this mechanism, recent evidence shows that firms with lower emissions intensity tend to have higher marginal products (Kim, 2025; Klenow, Pastén, and Ruane, 2024). Together, these channels suggest that climate policy uncertainty may have persistent adverse effects on economic performance.

Empirically, we find strong evidence that TFP declines persistently in response to climate policy uncertainty, supporting this interpretation. Figure 15a shows the impulse response of aggregate total factor productivity (TFP), as constructed by Fernald (2014), estimated in the time series. After a climate policy uncertainty shock, TFP falls significantly and persistently. We confirm this pattern at the firm level. Using the Compustat data, we compute firm-level TFP as the Solow residual. We find that climate policy uncertainty causes a marked and persistent fall in firm-level TFP on average, as shown in

Figure 15: Climate policy uncertainty and TFP

(a) Aggregate TFP (b) Firm-level TFP



Notes: Impulse responses of aggregate and firm-level TFP to a climate policy uncertainty shock, estimated using local projections on the aggregated climate policy uncertainty shock. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

Figure 15b.

6. Conclusion

We document climate policy uncertainty as a salient and economically important dimension of policy uncertainty. Using a novel index of climate policy uncertainty, combined with a narrative-based instrument constructed from major U.S. climate policy events, we isolate exogenous fluctuations in climate policy uncertainty. We show that an increase climate policy uncertainty leads to reduced industrial production, GDP, and private investment, while unemployment and prices rise. These effects reveal a distinct transmission mechanism: unlike other policy uncertainty shocks, climate policy uncertainty propagates primarily through supply-side channels rather than aggregate demand.

The adverse economic effects weigh down on aggregate emissions, but this comes at a substantial economic cost. The emissions intensity shows no improvement and, if anything, increases slightly. At the disaggregated level, we find evidence consistent with a green paradox: investment rises in fossil-related sectors such as mining, oil, and utilities following an increase in climate policy uncertainty. This pattern points to potentially larger long-term economic costs of climate policy uncertainty through misallocative forces.

Our results have clear implications for policymakers. First, they show that unclear and unpredictable climate policies carry tangible macroeconomic costs. Reducing uncertainty and providing a stable and predictable regulatory environment can help limit these costs during the climate transition. Second, the findings point to a nuanced role for monetary policy. Unlike conventional uncertainty shocks, which primarily depress demand and can be offset by accommodative monetary policy, climate policy uncertainty operates through supply-side channels, creating a trade-off between stabilizing output and containing inflation. This limits the scope for monetary accommodation and underscores the importance of predictable climate policy in mitigating transition costs.

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Online Appendix

The Macroeconomic Effects of Climate Policy Uncertainty

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Contents

A. Climate policy uncertainty and sentiment indices

In this appendix, we provide a description of the methodology used to construct the climate policy uncertainty and sentiment indices. Both indices rely on dictionaries for the concepts "climate change" and "policy" (or "climate policy") to identify relevant articles. The uncertainty index measures the occurrence of additional uncertainty-related concepts in the climate policy articles, while the sentiment index measures the extent of positive and negative sentiment across the same articles.

A.1. Climate change, policy, and climate policy dictionaries

To construct climate change, policy, and climate policy dictionaries, we use the following method. First, we preprocess articles published by news agencies that specialize in climate policy reporting. Second, we identify frequently-mentioned unigrams, bigrams, and trigrams to create a comprehensive *climate policy n-gram corpus*. Third, we identify distinct climate change, policy, and climate policy concepts from the *n*-grams, accounting for the overlap of terms across the *n*-grams. Finally, we generate broad and narrow versions of the dictionaries, with the goal of reducing false negatives and false positives, respectively.

A.1.1. Preprocessing the climate news corpus

We process news articles from agencies specializing in climate policy reporting, including *Inside Climate News*, *Inside EPA*, and *Washington Week (Energy)*, accessed through *Factiva* news archives. These agencies cover nationwide climate policy developments across a broad range of climate-related issues. Our selection of agencies allows us to focus on concepts relevant to national climate policy rather than state policy or local climate concerns. We keep the preprocessing straightforward, focusing on splitting contractions and tokenization.

A.1.2. Identifying frequently-mentioned unigrams, bigrams, and trigrams

Next, we identify unigrams, bigrams, and trigrams (henceforth, *n*-grams) in the articles. By doing so, we generate a comprehensive *climate policy n-gram corpus*. For each *n*-gram, we also obtain its frequency of occurrence across articles. The procedure we use for each *n*-gram is as follows.

- *Unigrams:* Unigrams are single words in the articles. To obtain the relevant unigrams, we process the universe of unigrams by excluding stop words, words that are less than two letters, and words that are fully composed of punctuations and numbers.

- *Bigrams:* Bigrams are two adjacent words in the articles. To obtain the relevant bigrams, we process the universe of bigrams by excluding bigrams that contain stop words, words that are less than two letters, and words that are fully composed of punctuations and numbers. Note that we also modify "hyphen tokens" before generating the bigrams set, allowing us to capture concepts such as "carbon-neutral" and "carbon neutral" consistently as "carbon neutral".

- *Trigrams:* Trigrams are three adjacent words in the articles. To obtain the relevant trigrams, we process the universe of trigrams by excluding trigrams that start or end with stop words and contain words that are less than two letters and words that are fully composed of punctuations and numbers. Similar to bigrams, we modify "hyphen tokens" before generating the trigrams set. Importantly, our trigrams allow for stop words as the center word, enabling us to capture concepts such as "cap and trade".

For example, "... greenhouse gas emission ..." gives us one trigram ("greenhouse gas emission"), two bigrams ("greenhouse gas" and "gas emission"), and three unigrams ("greenhouse", "gas", and "emission") while "... cap and trade ..." gives us one trigram ("cap and trade") and two unigrams ("cap" and "trade").

A.1.3. Identifying climate change, policy, and climate policy concepts

To identify climate change, policy, and climate policy concepts, we follow a method similar to that proposed by Aruoba and Drechsel (2024).[1] We begin by ranking each set of n-grams by their total frequency of occurrence across time. We then start with the most frequent n-gram and move down, selecting concepts relevant to climate change, policy, and climate policy and stopping at a generous lower bound.[2] Sometimes, as in previous examples, there are concepts that overlap across n-grams for a given dictionary, in which case we use the following algorithm.

[1] Aruoba and Drechsel (2024) use this method to identify frequently discussed concepts in documents prepared by the Federal Reserve staff ahead of policy decisions.

[2] Multiple authors went through this selection independently and discussed disagreements. We manually look through the top 500 unigrams, top 400 bigrams, and top 300 trigrams.

- *Trigrams:* We start with the trigrams set and work down from the most frequent terms to select relevant concepts. If the unigrams or bigrams that comprise a given trigram are *not vague in isolation*, we consider including them directly so as to capture all occurrences associated with the term. Going back to the previous example, we only include "cap and trade" as a climate policy concept since neither "cap" nor "trade" are sufficiently specific concepts regarding climate policy. However, for "greenhouse gas emission", we include "greenhouse gas" and "emission" as climate change concepts since both terms are sufficiently specific concepts regarding climate change.[3] Note that such exemptions are not the norm in our procedure, and mostly pertain to climate change concepts.

- *Bigrams:* Next, we proceed to the bigrams set and work down from the most frequent terms to select relevant concepts. If the unigrams that comprise a given bigram are not vague in isolation, we consider including them directly so as to capture all occurrences associated with the term. For example, instead of the bigram "epa administrator", we include the unigram "epa" as a climate policy concept since it is a sufficiently specific concept regarding climate policy.

- *Unigrams:* Next, we proceed to the unigrams set and work down from the most frequent terms to select relevant concepts, that are not vague in isolation.

Finally, we add plural forms and related variants of the selected concepts to the dictionary.

A.1.4. Building the climate change, policy, and climate policy dictionaries

After identifying the climate change, policy, and climate policy concepts, we build two dictionaries. The *broad dictionary*, designed to minimize false negatives, includes 120 concepts, while the *narrow dictionary*, designed to minimize false positives, includes 97 concepts.

- **Broad dictionary:** The broad dictionary ensures a comprehensive coverage of climate policy concepts, whilst minimizing the likelihood of false negatives. Our algorithm results in the selection of 41 concepts for the climate change dictionary, 42 concepts for the policy dictionary, and 37 concepts for the climate policy dictionary.

[3] Recall that "greenhouse gas emission" gives us one trigram ("greenhouse gas emission"), two bigrams ("greenhouse gas" and "gas emission"), and three unigrams ("greenhouse", "gas", and "emission"). By selecting "greenhouse gas" and "emission" as the concepts, we effectively capture all but individual occurrences of "greenhouse" and "gas", concepts which are not sufficiently specific to warrant inclusion.

- **Narrow dictionary:** The narrow dictionary is aimed at refining the search queries to minimize the likelihood of false positives. Our algorithm results in the selection of 42 concepts for the climate change dictionary, 29 concepts for the policy dictionary, and 26 concepts for the climate policy dictionary.

Figure 1 in the main text and Figure A.1 present the word clouds for the broad and narrow dictionaries, respectively, where the size of the dictionary concept represents the frequency of its occurrence across articles. For example, the broad version includes "carbon" in the climate change dictionary, while the narrow version instead includes "carbon dioxide", "carbon reduction", "low carbon", "carbon capture", and "carbon sequestration". Similarly, the broad version includes "emission", while the narrow version instead includes "carbon emission", "methane emission", "emission reduction", and "emission control".

Figure A.1: Climate policy dictionary: Broad version

(a) Climate change (b) Policy (c) Climate policy

Notes: Each panel shows the most common concepts in the broad versions of the climate, policy, and climate policy dictionaries derived from the climate policy news corpus. The size of the concept reflects its frequency across the corpus.

By manually applying judgment-based restrictions to the concepts, we can systematically and comprehensively capture climate policy concepts while maintaining the interpretability of dictionary-based indices. The specificity of concepts in the narrow dictionary reduces the risk of false positives and is therefore our preferred version for the baseline analysis. Table A.1 summarizes the concepts included in the broad and narrow dictionaries. We also allow for standard linguistic variations of these terms, including plurals and adjectival forms.

Table A.1: Overview of dictionary concepts

Dictionary	Level	Broad dictionary terms	Narrow dictionary terms
Climate	Trigrams	capture and sequestration, climate and energy, sea level rise	capture and sequestration, climate and energy, sea level rise
	Bigrams	climate change, climate crisis, climate disaster, climate science, climate scientist, climate action, global warming, climate warming, temperature rise, global temperature, greenhouse gas, renewable energy, renewable fuel, renewable electricity, renewable power, clean energy, clean power, green energy, energy efficiency, fuel economy, fuel efficiency, fossil fuel, energy transition, climate transition, climate mitigation, climate adaptation, climate accord, climate conference, climate activist, climate demonstration	climate change, climate crisis, climate disaster, climate science, climate scientist, climate action, global warming, climate warming, temperature rise, greenhouse gas, renewable energy, renewable fuel, renewable electricity, renewable power, clean energy, clean power, green energy, energy efficiency, fuel economy, fuel efficiency, fossil fuel, energy transition, climate transition, climate mitigation, climate adaptation, climate accord, climate conference, low carbon, carbon emission, carbon dioxide, carbon reduction, methane emission, emission reduction, emission control, carbon capture, carbon sequestration
	Unigrams	ghg, co2, carbon, emission, methane, environmental, decarbonization, renewables	ghg, co2, decarbonization
Policy	Trigrams	house and senate, president joe biden, president donald trump, president barack obama, president george bush, president bill clinton, president ronald reagan	house and senate, president joe biden, president donald trump, president barack obama, president george bush, president bill clinton, president ronald reagan

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Table A.1: Overview of dictionary concepts

Dictionary	Level	Broad dictionary terms	Narrow dictionary terms
Policy	Bigrams	white house, biden administration, president biden, trump administration, president trump, obama administration, president obama, bush administration, president bush, clinton administration, president clinton, reagan administration, president reagan, administration official, federal agency, state department, house bill, executive order, tax credit, proposed rule, federal appeal, columbia circuit	white house, biden administration, president biden, trump administration, president trump, obama administration, president obama, bush administration, president bush, clinton administration, president clinton, reagan administration, president reagan, federal agency, house bill, senate bill, executive order, tax credit, proposed rule
	Unigrams	policy, legislation, law, congress, senate, regulation, government, reform, subsidy, rulemaking, court, litigation, ruling	legislation, congress, regulation
Climate policy	Trigrams	environmental protection agency, energy department, cap and trade, clean power plan, energy efficiency program, fuel economy standard, climate change bill, clean air act, climate stewardship act, clear skies act	environmental protection agency, cap and trade, clean power plan, fuel economy standard, climate change bill
	Bigrams	energy policy, energy legislation, energy law, energy tax, energy committee, climate bill, climate policy, climate legislation, climate rule, carbon tax, carbon price, carbon market, carbon trading, carbon limit, emission trading, emission limit, emission permit, emission standard, ghg rule, ghg limit, ghg permit, ghg standard, fuel standard, waxman markey, kerry lieberman	climate bill, climate policy, climate legislation, climate rule, environmental law, environmental policy, carbon tax, carbon price, carbon market, carbon trading, carbon limit, emission trading, emission limit, emission permit, emission standard, ghg rule, ghg limit, ghg permit, ghg standard, fuel standard
	Unigrams	epa, doe	epa

A.2. Constructing the climate policy uncertainty indices

A.2.1. Identifying climate policy uncertainty articles

Our baseline monthly index of climate policy uncertainty is derived from a dataset comprising 7.87 million news articles published between 1985 and 2025, with an average of 16,300 articles per month. These articles are sourced from four leading newspapers—the *New York Times*, the *Wall Street Journal*, the *Washington Post*, and the *Los Angeles Times*—and accessed through *ProQuest U.S. Newsstream*.[4] We denote this dataset as $\mathcal{A}$.

To identify articles that discuss climate policy uncertainty, we first construct a subset, denoted as set $\mathcal{B}$, consisting of articles that discuss climate policy *news*. An article is included in this subset if it contains concepts from the predefined dictionaries, according to the following criteria:

(Climate change dictionary **AND** Policy dictionary)
OR Climate policy dictionary

Subsequently, an article in set $\mathcal{B}$ is classified as discussing climate policy uncertainty if it additionally contains concepts from the uncertainty dictionary. The refined search criteria is as follows:

(Climate change dictionary **AND** Policy dictionary **AND** Uncertainty dictionary)
OR (Climate policy dictionary **AND** Uncertainty dictionary),

where, the uncertainty dictionary, following Baker, Bloom, and Davis (2016), consists of the terms "uncertain', "uncertainty", and "uncertainties".

A.2.2. Constructing the indices

To construct the composite climate policy uncertainty (CPU) indices, we proceed as follows, drawing on the approach by Baker, Bloom, and Davis (2016). First, we scale the number of articles on climate policy uncertainty by the total number of articles published in the same newspaper and over the same month. Second, we standardize the resulting series for each newspaper to have a unit standard deviation from 1985 to 2019. Third, we average these standardized series across all newspapers for each month.[5] Finally, we normalize the averaged series to have a mean value of 100 from 1985 to 2019.

[4] The *New York Times*, the *Wall Street Journal*, the *Washington Post*, and the *Los Angeles Times* are the four largest newspapers by print circulation and subscriber count as of 2023.

[5] Since our baseline measure relies on four leading newspapers, we weight each source equally. Note that *ProQuest U.S. Newsstream* includes the *Washington Post* only from 1987 onward. Therefore, for 1985 and 1986, the average is computed using the *New York Times*, the *Wall Street Journal*, and the *Los Angeles Times*.

A.2.3. Audit methodology

Alternative news archive. We construct the baseline CPU index using newspaper articles in the *New York Times*, the *Wall Street Journal*, the *Washington Post*, and the *Los Angeles Times*, accessed through *ProQuest U.S. Newsstream*. As an alternative, we construct the CPU index using newspaper articles in the *Wall Street Journal* and the *Washington Post*, obtained via the *Factiva API*, which provides access to the full text of articles. Our baseline index exhibits a correlation of about 0.9 with the Factiva index, mainly reflecting the differences in the considered set of newspapers.

LLM audit. To evaluate the performance of our index, which is constructed using an automated text-search algorithm, we randomly sample 2000 articles from the set of climate policy uncertainty articles. We then use the `gpt-4o-mini` model, accessed through the *OpenAI API*, to identify if an article discusses uncertainty regarding the climate policy. Our prompt engineering process involved experimenting with prompts of varying specificity and output structures, as well as incorporating feedback from human validation of initial outputs. Our approach builds on Baker, Bloom, and Davis (2016), Caldara and Iacoviello (2022), and Caldara, Iacoviello, and Yu (2024), who employ similar prompts for human and LLM audit exercises.

We also use a number of safeguards to ensure accuracy of the model output. First, to limit hallucination and increase precision, we feed in the full text of the articles individually. As we require the full text of the articles for this exercise, we rely on articles from the *Wall Street Journal* and the *Washington Post* accessed through the *Factiva API*. Second, we keep the temperature parameter of the model low, to ensure focused and deterministic responses. Finally, we instruct the model to provide a brief explanation to allow for human validation of the output. The prompt we feed in is as follows:

> "I'm providing an article that discusses policy measures related to climate change. The article does not need to focus primarily on climate policy; it is sufficient if the topic appears in some paragraphs.
>
> Your task is to determine whether the article discusses uncertainty, risk, or ambiguity about the climate policy.
>
> Return your response as a JSON object in the following format:
>
> ```
> {"classification": <number>,
> "explanation": <"brief explanation (1-2 sentences)">}
> ```
>
> Classification values:

- 1 = Yes (the article discusses uncertainty about climate policy);
- 0 = No (the article does not discuss uncertainty about climate policy);
- 99 = Unsure.

Ensure the output is a valid JSON object with no extra text."

Based on the LLM classification, the false discovery rate of our baseline index is around 20%, implying a precision of approximately 80%. This lies squarely within the range typically observed for text-based indices in the literature.

Human audit methodology. To evaluate the performance of the LLM, we use a sample of 200 articles from the LLM audit and manually assess whether each article discusses uncertainty in relation to the climate policy. To ensure the accuracy of the audit, each article is independently evaluated by multiple auditors. The instructions provided to the auditors are as follows and closely align with the prompt given to the LLM:

> "We randomly sampled a subset of articles discussing policy measures related to climate change, as provided in the accompanying Excel file. Each article should be evaluated for whether it discusses uncertainty, risk, or ambiguity about the climate policy, using the following classification:
>
> - 1 = Yes (the article discusses uncertainty about climate policy);
> - 0 = No (the article does not discuss uncertainty about climate policy);
> - 99 = Unsure.
>
> Articles that are reviews, historical accounts, meeting or talk summaries, or anniversary pieces should be coded as 1 (Yes) only if they explicitly highlight uncertainty regarding *recent, current, or future climate policy*. The audit results should be recorded in the Excel file, with two additional columns:
>
> - `cpu_ind` (classification value as per the above guidelines).
> - `cpu_ind_expln` (a brief explanation of the classification, 1-2 sentences)."

The human audit results indicate that the LLM reliably identifies articles that discuss uncertainty about climate policy. While some differences between the LLM and human classifications occur, the overall alignment is strong (over 80%). The alignment is comparable to typical agreement rates among human annotators, reflecting also the inherent nuances involved in interpreting uncertainty.

The findings thus reinforce the validity of the LLM's results and demonstrate that it serves as a credible tool for validating climate policy uncertainty in large text corpora, when used with appropriate safeguards and carefully designed prompts.

A.3. Constructing the climate policy sentiment index

A.3.1. Identifying climate policy articles

Our monthly index of climate policy sentiment is derived from a dataset comprising of 3.75 million news articles published between 1985 and 2020, with an average of 8,670 articles per month. These articles are sourced from two leading newspapers—the *Wall Street Journal* and *Washington Post*—obtained via the *Factiva API*, which provides access to the full text of articles.

To identify sentiment around climate policy, we first construct a set of articles that discuss climate policy *news*. An article is included in this set if it contains concepts from the predefined *narrow* dictionaries according to the following criteria:

(Climate change dictionary **AND** Policy dictionary)
OR Climate policy dictionary

A.3.2. Identifying sentiment

We quantify sentiment toward climate policy by analyzing the context surrounding each policy concept in articles discussing climate policy news, following an approach similar to Hassan et al. (2019) and Aruoba and Drechsel (2024).

First, we define positive and negative terms using the Loughran and Mcdonald (2011) dictionary. Second, for each sentence containing a policy (or climate policy) concept, we examine a window of 10 words before and after the concept to identify co-occurrences with the positive or negative terms. Third, for each concept, we calculate a normalized sentiment score by assigning $+1$ for each positive term and -1 for each negative term, then dividing the sum by the total number of words in the n-gram representing that concept. Finally, we sum the normalized sentiment scores across all identified policy concepts in the article to obtain an article-level climate policy sentiment measure. This approach captures both the direction and intensity of sentiment while ensuring comparability across articles of different lengths and policy concepts of different n-gram lengths.

A.3.3. Constructing the index

To construct the composite climate policy sentiment index, we proceed as follows, again drawing on the approach by Baker, Bloom, and Davis (2016). First, we sum the normalized sentiment scores across all articles published in the same newspaper and over the same month. Second, we standardize the resulting series for each newspaper to have a unit standard deviation from 1985 to 2019. Third, we average these standardized series across all newspapers for each month. Finally, we normalize the averaged series to have a mean value of 100 from 1985 to 2019.

B. Instrument for climate policy uncertainty

In this appendix, we describe the methodology used to identify events that contribute to climate policy uncertainty. We then provide a detailed list and a summary of the events included in our dataset. Finally, we outline our procedure for constructing an instrumental variable capturing exogenous variation that plausibly induces U.S. climate policy uncertainty.

Sources. To identify events, we rely on websites of government administrations, congressional records, regulatory agencies, courts, and newspapers. Additionally, to ensure a comprehensive coverage of the events, we corroborate our primary research using secondary sources, such as the Center for Climate and Energy Solutions, Congressional Research Service, the Environmental and Energy Study Institute, and the Legal Planet.

B.1. Event selection methodology

In this section, we outline the methodology for selecting events across five categories—international agreements, judicial actions, legislative actions, presidential actions, and regulatory actions—that have contributed to U.S. climate policy uncertainty. When selecting events, we adopt an agnostic approach to ensure a comprehensive representation of policy-relevant actions. Importantly, we identify events that both generate and resolve climate policy uncertainty.

International agreements and treaties. This category includes landmark bilateral and multilateral agreements, conventions, mandates, protocols, and treaties, as well as their ratifications, where applicable. Events generally fall into six types: announcements (statements of intent or policy positions), negotiation mandates (formal authorizations directing future talks), agreements (commitments with varying levels of legal obligation), signatures (formal signing of agreements), ratifications (official Senate approval or equivalent), and executive actions (steps taken by the executive branch to implement or enter agreements).

Judicial actions. This category encompasses court decisions that have directly influenced U.S. climate policy by upholding, restricting, or suspending regulatory actions. While most events are final rulings, we also include notable exceptions such as case filings and stay orders that temporarily halt implementation.

Legislative actions. This category tracks climate-related bills introduced in the U.S. Congress, starting with the first introduction of a measure in the chamber of origin, along with any formal proposals, press releases, or public announcements preceding the official introduction, if applicable. Key legislative outcomes are included, such as passage in one or both chambers, formal signing by the President, or, where applicable, stalling or blocking of the measure. In addition, we include select measures from California that played a pivotal role in shaping federal climate policy. Routine elements—such as committee discussions, conference reports, and concurrence on amendments after initial passage, are excluded—ensuring the dataset captures only the most salient legislative events that signal meaningful movement in climate policy.

Presidential actions. This category covers major climate-related initiatives by U.S. Presidents, including formal statements, policy proposals, and executive measures aimed at guiding or implementing climate policies. Events are classified as announcements (statements of intent or policy positions), policy proposals (plans introduced to shape future legislation or regulation), and executive actions (directives enforcing or implementing policy).

Regulatory actions. This category covers climate-related rule-makings and decisions issued by federal agencies such as the EPA, DOT, and DOI. We track regulatory events through their complete lifecycle—from the initial proposal and public comment periods to final rule issuance. We also include notices of intent to reconsider or revise standards, as well as any subsequent revisions or withdrawals. Additionally, we incorporate waiver decisions, especially those involving California's unique authority to implement vehicle emissions standards that are stricter than the federal baseline. Given California's long-standing leadership and influence on national climate policy, select regulatory actions and waiver approvals or denials are included to provide a comprehensive view of the U.S. federal regulatory landscape.

B.2. Dataset and summary of climate policy uncertainty events

Table B.1 presents the events we identify as contributing to climate policy uncertainty, while Table B.2 provides a detailed classification of the events identified.

Table B.1: Climate policy uncertainty events

	Date	Event overview
1	1987-09-16	Montreal Protocol signed by Reagan
2	1988-03-14	Montreal Protocol ratified by the Senate
3	1988-06-23	Senate testimony by Hansen
4	1989-01-09	Global Change Research Act of 1990 proposed
5	1989-01-25	Global Change Research Act of 1990 introduced in the Senate
6	1990-02-06	Global Change Research Act of 1990 passed by the Senate
7	1990-06-26	Ban on new offshore drilling issued by Bush
8	1990-10-26	Global Change Research Act of 1990 passed by the House
9	1990-11-16	Global Change Research Act of 1990 signed by Bush
10	1991-02-04	Energy Policy Act of 1992 introduced in the House
11	1992-05-27	Energy Policy Act of 1992 passed by the House
12	1992-06-12	UN Framework Convention on Climate Change (UNFCCC) signed by Bush at the Rio Earth Summit
13	1992-07-30	Energy Policy Act of 1992 passed by the Senate
14	1992-10-07	UN Framework Convention on Climate Change (UNFCCC) ratified by the Senate
15	1992-10-24	Energy Policy Act of 1992 signed by Bush
16	1993-02-17	BTU tax proposed by Clinton
17	1993-04-21	Emissions reduction pledge announced by Clinton
18	1993-05-25	BTU tax introduced in the House
19	1993-05-27	BTU tax passed by the House
20	1993-06-08	BTU tax withdrawn by Clinton
21	1993-10-19	Climate Change Action Plan (CCAP) announced by Clinton
22	1995-04-07	Berlin Mandate adopted (COP1)
23	1996-07-17	U.S. signals support for binding targets (COP2)
24	1997-06-12	Byrd-Hagel Resolution introduced in the Senate
25	1997-07-25	Byrd-Hagel Resolution passed by the Senate
26	1997-10-22	Climate Change Proposal announced by Clinton
27	1997-12-10	Kyoto Protocol agreement announced by Clinton (COP3)
28	1998-06-12	Ban on new offshore drilling extended by Clinton
29	1998-11-12	Kyoto Protocol signed by Clinton

Continued on next page

Table B.1: Climate policy uncertainty events

	Date	Event overview
30	1999-01-19	Climate change initiatives announced by Clinton
31	2001-02-23	California's Clean Car Standards (Pavley regulations) introduced in the Assembly
32	2001-03-13	Kyoto Protocol opposition announced by Bush
33	2001-06-06	California's Clean Car Standards (Pavley regulations) passed by the Assembly
34	2002-06-29	California's Clean Car Standards (Pavley regulations) passed by the Senate
35	2002-07-22	California's Clean Car Standards (Pavley regulations) signed by the Governor
36	2003-01-09	McCain-Lieberman Climate Stewardship Act of 2003 introduced in the Senate
37	2003-10-30	McCain-Lieberman Climate Stewardship Act of 2003 blocked in the Senate
38	2004-09-23	California's Clean Car Standards (Pavley regulations) adopted by the CARB
39	2004-12-06	California's Global Warming Solutions Act of 2006 introduced in the Assembly
40	2005-02-10	McCain-Lieberman Climate Stewardship Act of 2005 introduced in the Senate
41	2005-04-11	California's Global Warming Solutions Act of 2006 passed by the Assembly
42	2005-04-18	Energy Policy Act of 2005 introduced in the House
43	2005-04-21	Energy Policy Act of 2005 passed by the House
44	2005-05-26	McCain-Lieberman Climate Stewardship and Innovation Act of 2005 introduced in the Senate
45	2005-06-21	McCain-Lieberman Amendment to the Energy Policy Act of 2005 introduced in the Senate
46	2005-06-22	McCain-Lieberman Amendment to the Energy Policy Act of 2005 blocked in the Senate
47	2005-06-28	Energy Policy Act of 2005 passed by the Senate
48	2005-08-08	Energy Policy Act of 2005 signed by Bush
49	2005-12-20	Regional Greenhouse Gas Initiative (RGGI) MOU signed
50	2005-12-21	Waiver of federal preemption for motor vehicle GHG emissions regulations requested by California
51	2006-08-30	California's Global Warming Solutions Act of 2006 passed by the Senate
52	2006-09-20	Lawsuit against automakers for global warming damages filed by California
53	2006-09-27	California's Global Warming Solutions Act of 2006 signed by the Governor
54	2007-01-12	Energy Independence and Security Act of 2007 introduced in the House
55	2007-01-12	McCain-Lieberman Climate Stewardship and Innovation Act of 2007 introduced in the Senate
56	2007-01-16	Sanders-Boxer Global Warming Pollution Reduction Act of 2007 introduced in the Senate
57	2007-01-18	Energy Independence and Security Act of 2007 passed in the House
58	2007-01-19	Major corporations and NGOs unite to support federal climate policy (U.S. Climate Action Partnership)
59	2007-04-02	Massachusetts v. EPA
60	2007-06-21	Energy Independence and Security Act of 2007 passed in the Senate

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Table B.1: Climate policy uncertainty events

	Date	Event overview
61	2007-10-18	Lieberman-Warner Climate Security Act of 2007 introduced in the Senate
62	2007-12-19	Energy Independence and Security Act of 2007 signed by Bush
63	2007-12-19	Waiver of federal preemption for California's motor vehicle GHG emissions regulations rejected
64	2008-05-20	Lieberman-Warner Climate Security Act of 2008 introduced in the Senate
65	2008-06-06	Lieberman-Warner Climate Security Act of 2008 stalled in the Senate
66	2008-07-14	Ban on new offshore drilling withdrawn by Bush
67	2008-11-17	U.S. climate leadership affirmed by Obama
68	2008-12-18	Interpretation of "Regulated Pollutant" under PSD permit program announced by the EPA
69	2009-03-31	Waxman-Markey American Clean Energy and Security Act of 2009 proposed
70	2009-05-15	Waxman-Markey American Clean Energy and Security Act of 2009 introduced in the House
71	2009-05-19	National Fuel Efficiency Policy announced by Obama
72	2009-06-26	Waxman-Markey American Clean Energy and Security Act of 2009 passed by the House
73	2009-06-30	Waiver of federal preemption for California's motor vehicle GHG emissions regulations granted
74	2009-09-15	GHG emissions and CAFE standards for light-duty vehicles ("Tailpipe Rule") proposed by the EPA and DOT
75	2009-09-30	GHG Tailoring Rule proposed by the EPA
76	2009-10-10	Bipartisan climate framework announced by Kerry and Graham
77	2009-11-17	U.S.-China clean energy announcement
78	2009-12-07	GHG Endangerment Finding finalized by the EPA
79	2009-12-18	Copenhagen Accord announced by Obama (COP15)
80	2010-03-31	Ban on new offshore drilling extended in sensitive areas by Obama, along with expansion of selective leasing
81	2010-04-01	GHG emissions and CAFE standards for light-duty vehicles ("Tailpipe Rule") finalized by the EPA and DOT
82	2010-04-24	Bipartisan climate framework collapses as Graham withdraws support
83	2010-05-12	Kerry-Lieberman American Power Act proposed
84	2010-05-13	GHG Tailoring Rule finalized by the EPA
85	2010-05-21	National Fuel Efficiency Standards for heavy-duty and next-phase light-duty vehicles announced by Obama
86	2010-07-22	Climate change bills effectively abandoned in the Senate
87	2010-10-25	GHG emissions and CAFE standards for medium- and heavy-duty vehicles proposed by the EPA and DOT
88	2010-12-01	Ban on new offshore drilling extended by Obama

Continued on next page

Table B.1: Climate policy uncertainty events

	Date	Event overview
89	2010-12-16	Cap-and-trade regulation adopted by the CARB
90	2011-02-02	Upton-Whitfield-Inhofe Energy Tax Prevention Act of 2011 proposed
91	2011-03-03	Upton-Whitfield-Inhofe Energy Tax Prevention Act of 2011 introduced in the House
92	2011-04-07	Upton-Whitfield-Inhofe Energy Tax Prevention Act of 2011 passed by the House
93	2011-06-20	American Electric Power Company v. Connecticut
94	2011-07-29	National Fuel Efficiency Standards agreement for next-phase light-duty vehicles announced by Obama
95	2011-08-09	GHG emissions and CAFE standards for medium- and heavy-duty vehicles finalized by the EPA and DOT
96	2011-11-16	GHG emissions and CAFE standards for light-duty vehicles (Phase 2) proposed by the EPA and DOT
97	2012-01-18	Keystone XL Pipeline completion blocked
98	2012-01-26	Advanced Clean Cars (ACC) program standards adopted by the CARB
99	2012-03-27	Carbon pollution standards for new power plants (NSPS) proposed by the EPA
100	2012-06-26	Coalition for Responsible Regulation v. EPA
101	2012-08-28	GHG emissions and CAFE standards for light-duty vehicles (Phase 2) finalized by the EPA and DOT
102	2012-12-27	Waiver of federal preemption for California's motor vehicle GHG emissions regulations granted
103	2013-02-14	Sanders Sustainable Energy Act of 2013 introduced in the Senate
104	2013-02-14	Sanders-Boxer Climate Protection Act of 2013 introduced in the Senate
105	2013-06-08	U.S.–China agreement to phase down HFCs
106	2013-06-25	Climate Action Plan announced by Obama
107	2013-09-20	Carbon pollution standards for new power plants (NSPS) revised by the EPA
108	2014-06-02	Carbon pollution standards for existing power plants (Clean Power Plan; CPP) proposed by the EPA
109	2014-06-23	Utility Air Regulatory Group (UARG) v. EPA
110	2014-11-11	U.S.-China climate change announcement
111	2014-12-16	Ban on new offshore drilling extended by Obama
112	2015-01-14	Methane emissions reduction target announced by Obama
113	2015-01-27	Ban on new offshore drilling extended by Obama
114	2015-03-31	Emissions reduction target for 2025 reported to the UNFCCC
115	2015-06-19	GHG emissions and CAFE standards for medium- and heavy-duty vehicles (Phase 2) proposed by the EPA and DOT
116	2015-08-03	Carbon pollution standards for new (NSPS) and existing power plants (CPP) finalized by the EPA
117	2015-08-18	Methane emissions standards proposed by the EPA

Continued on next page

Table B.1: Climate policy uncertainty events

	Date	Event overview
118	2015-09-25	U.S.-China climate change announcement
119	2015-11-29	Mission Innovation initiative launched to accelerate global clean energy innovation
120	2015-12-12	Paris Climate Agreement announced by Obama (COP21)
121	2016-01-21	Methane waste prevention rule proposed by the DOI
122	2016-02-04	Clean Transportation System proposed by Obama
123	2016-02-09	Clean Power Plan (CPP) halted by the Supreme Court (West Virginia v. EPA)
124	2016-04-22	Paris Climate Agreement signed by Obama
125	2016-05-12	Methane emissions standards finalized by the EPA
126	2016-08-16	GHG emissions and CAFE standards for medium- and heavy-duty vehicles (Phase 2) finalized by the EPA and DOT
127	2016-09-03	Paris Climate Agreement formally entered under executive action by Obama
128	2016-09-09	Offshore Wind Energy Strategy announced by DOE and DOI
129	2016-11-14	Methane waste prevention rule finalized by the DOI
130	2016-12-04	Dakota Access Pipeline completion blocked
131	2016-12-20	Ban on new offshore drilling extended by Obama
132	2017-01-24	Energy and infrastructure projects accelerated by Trump
133	2017-03-03	Midterm evaluation determination of GHG emissions and CAFE standards reconsidered by the EPA and DOT
134	2017-03-28	Energy Independence Policy announced by Trump
135	2017-06-01	Paris Climate Agreement withdrawal by Trump
136	2017-10-10	Clean Power Plan (CPP) repeal proposed by the EPA
137	2017-12-07	GHG Endangerment Finding challenged by the EPA administrator Pruitt
138	2018-04-02	Midterm evaluation determination of GHG emissions and CAFE standards withdrawn by the EPA
139	2018-08-01	Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule proposed by the EPA and DOT
140	2018-08-20	Affordable Clean Energy (ACE) Rule proposed by the EPA
141	2018-09-18	Methane waste prevention rule rolled back by the DOI
142	2019-02-07	Green New Deal (GND) introduced in the House
143	2019-03-26	Green New Deal (GND) stalled in the Senate
144	2019-06-19	Clean Power Plan (CPP) repeal and Affordable Clean Energy (ACE) Rule finalized by the EPA
145	2019-09-18	Waiver of federal preemption for California's motor vehicle GHG emissions regulations rejected
146	2019-09-19	Safer Affordable Fuel-Efficient (SAFE) Vehicles Rule finalized by the EPA and DOT

Table B.2: Classification of climate policy uncertainty events

Event type	Count
Advocacy	**2**
International agreements and treaties	**20**
Agreement	3
Announcement	8
Executive action	2
Negotiation Mandate/Decision	1
Ratification	2
Signature	4
Judicial action	**6**
Decision	4
Filing	1
Stay order	1
Legislative action	**56**
Announcement	2
Blocked, stalled, or withdrawn	6
Introduced	21
Passed — Assembly	2
Passed — House	7
Passed — Senate	7
Proposed	5
Signed	6
Presidential action	**22**
Announcement	3
Executive action	12
Policy proposal	7
Regulatory action	**40**
Adoption	3
Announcement	2
Decision	5
Final rule	12
Interstate agreement	1
Memorandum	1
Notice of intent	1
Proposed rule	13
Request	1
Withdrawal	1
Total	**146**

B.3. Constructing the instrument

Event intensity. To quantify the importance of each event, we use the information contained in our corpus of 7.87 million news articles published in the print editions of leading American newspapers: the *New York Times* (NYT), the *Wall Street Journal* (WSJ), the *Washington Post* (WaPo), and the *Los Angeles Times* (LAT).

For each event identified in our dataset, we count the number of articles classified as relating to climate policy within a narrow window of the event. Recall that we classify an article as relating to climate policy if it contains at least one concept from each of the climate change and policy dictionaries, or if it contains at least one concept from the climate policy dictionary. We denote this count as $n^{\text{cp}}_{i,d}$, where $i \in \{\text{NYT}, \text{WSJ}, \text{WaPo}, \text{LAT}\}$ is the newspaper and d is the day relative to the event day.

In our baseline analysis, we use a window that includes the day of the event and the following day, i.e., $d \in \{0, 1\}$. This choice balances reducing background noise with allowing sufficient time for news outlets to report on the event. Our results remain robust to using a smaller window, i.e., the day of the event ($d \in \{0\}$) or a longer window, such as the day of the event and the following two days ($d \in \{0, 1, 2\}$).

Controlling for anticipatory effects. Policy developments may be at least partially anticipated before official announcements. To address this concern, we refine our identification strategy by subtracting the number of climate policy articles published in the two days preceding each event from those published on the event day and the following day:

$$n_{i,\text{Event}} = \sum_{d=0}^{1} n^{\text{cp}}_{i,d} - \sum_{d=-2}^{-1} n^{\text{cp}}_{i,d}$$

Here, $n_{i,\text{Event}}$ measures the *event intensity*, i.e., the intensity of reporting around a climate policy uncertainty event in newspaper i. This adjustment helps remove anticipatory effects, ensuring that our instrument captures only unanticipated increases in climate policy uncertainty.

Controlling for stringency. The raw event intensity measure could be potentially correlated with the first moment of climate policy—that is, with the expected direction and magnitude of climate policy news. To address this concern, we follow an approach similar in spirit to Hassan et al. (2019). We construct an event-level stringency index, to serve as a proxy for the first moment of climate policy, and residualize the event intensity with respect to the stringency index.

The stringency index captures the direction of policy news around each event: events signaling a tightening of policy are assigned a value of +1, those signaling a loosening are assigned -1, and events without a clear signal are assigned 0.[6] We then purge the event intensity of the effect of the stringency index as follows:

$$n_{i,\text{Event}} = \alpha_i + \beta_i \times \text{Stringency}_{\text{Event}} + \text{Uncertainty}_{\text{i, Event}}$$

Here, the *refined event intensity* measure, $\text{Uncertainty}_{\text{i, Event}}$, isolates some exogenous variation around an event that induces or lowers climate policy uncertainty and orthogonal to the first moment of climate policy news.

Normalization and aggregation. To account for the variation in the number of articles published across newspapers, we first scale the refined event intensity measure by the total number of articles published in the given newspaper over the month of the event.

Finally, following the methodology used in the construction of the climate policy uncertainty index, we standardize each newspaper-level series to unit standard deviation and then average across all the newspapers by event date. We then aggregate the daily event series to a monthly series by summing the normalized counts within a given month. In months with no events, the series is assigned a value of zero.

C. Data

C.1. Macro data

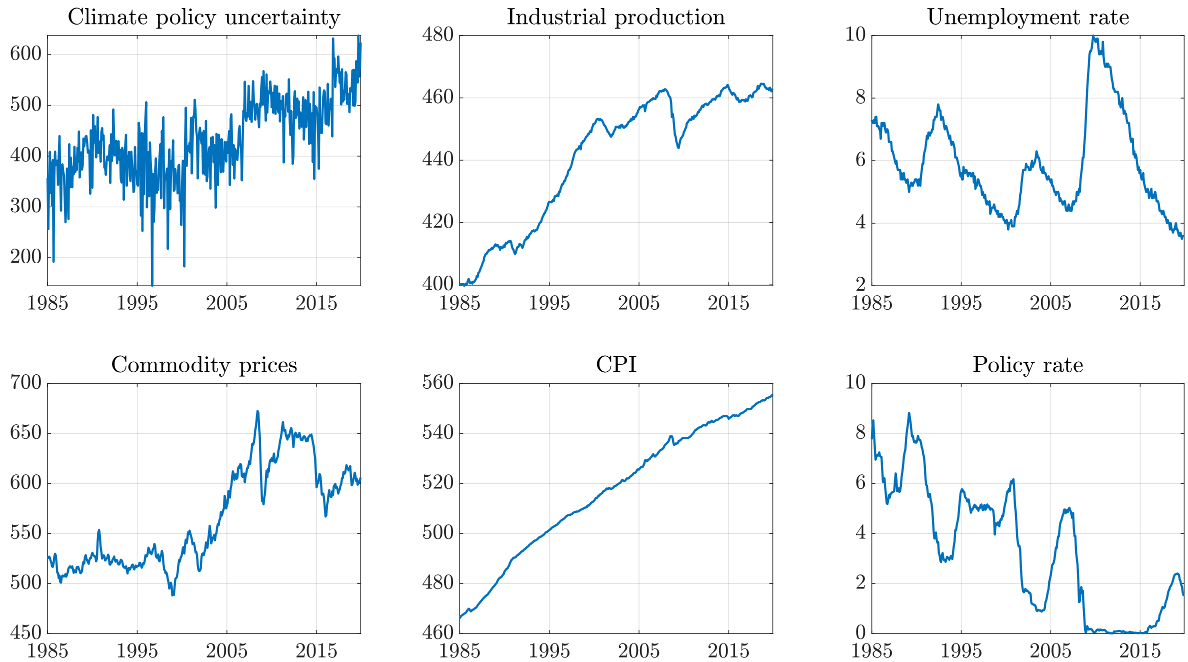
In this appendix, we provide more details on the macroeconomic data used in the paper, including information on the data sources and the transformations. Table C.1 lists the data sources and Figure C.1 displays the transformed data series in the VAR.

[6]This parsimonious classification provides a transparent way to capture the first moment of climate policy news. In Appendix D.2.1, we alternatively allow for richer measures that also incorporate the magnitude of policy changes, for example by assigning larger weights to more binding or consequential actions or by scaling stringency with the intensity of media coverage.

Table C.1: Macro data: Description and sources

Variable	Description	Source	Trans.
Uncertainty indicators			
CPU	News-based climate policy uncertainty index	ProQuest / own construction	100×log
CPN	News-based climate policy news index	ProQuest / own construction	100×log
CPS	News-based climate policy sentiment index	Factiva / own construction	100×log
EPU	News-based economic policy uncertainty index	Baker, Bloom, and Davis (2016)	100×log
TPU	News-based trade policy uncertainty index	Caldara et al. (2020)	100×log
GPR	News-based geopolitical risk index	Caldara and Iacoviello (2022)	100×log
VXO	CBOE S&P 100 volatility index, extended as in Bloom (2009)	FRED, Bloomberg	level
Macro indicators: Monthly			
INDPRO	Industrial production	FRED	100×log
UNRATE	Unemployment rate	FRED	level
SPGSCIIndex	S&P Goldman Sachs Commodity Index (GSCI)	Bloomberg	100×log
CPIAUCSL	Consumer price index for all urban consumers: All items in U.S. city average	FRED	100×log
TB3MS	3-month Treasury bill secondary market rate	FRED	level
UMCSENT	Consumer sentiment, Surveys of Consumers, University of Michigan	FRED	100×log
Macro indicators: Quarterly			
GDPC1	Real gross domestic product	FRED	100×log
EMISSCO2TOTVTTTOUSA	Total carbon dioxide emissions from all sectors, all fuels; temporally disaggregated using the Chow-Lin method with industrial production, producer prices, and energy consumption expenditures as indicators	FRED / own calculations	100×log
GPDIC1	Real gross private domestic investment	FRED	100×log
GCEC1	Real government consumption expenditures and gross investment	FRED	100×log
B358RG3Q086SBEA	Chain-type price index for gross value added (GDP) by non-farm business	FRED	100×log
TFP	Total factor productivity	Fernald (2014)	100×log
Other controls			
PCI	Partisan conflict index	Azzimonti (2018)	100×log
PoliticalParty	Indicator for incumbent party in the federal administration	House of Representatives	level
DisastersNum	Number of billion-dollar weather and climate disasters in the U.S.	NOAA	level
GlobalAnomalies	Global temperature anomalies	NOAA	level

Figure C.1: Transformed data series in VAR



C.2. Micro data

In this appendix, we provide detailed information on the micro data used in Section 5 of the paper. We also provide a summary of the variables and their definitions in Table C.2.

Compustat. We use the Compustat North American Fundamentals dataset, accessed through Wharton Research Data Services (WRDS), to analyze firm-level outcomes. Compustat Fundamentals provides standardized financial items covering income statement, balance sheet, and cash flow for all public companies, including active and inactive companies.

Our primary dataset is the quarterly Compustat Fundamentals. To ensure that we obtain unique observations, we use additional screening variables following the WRDS guidelines. We filter on consolidated accounts (`consol = C`), industrial reporting format (`indfmt = INDL`), standardized data format (`datafmt = STD`), domestic companies (`popsrc = D`), and calendar view (`datacqtr` not null). This renders our dataset unique by the identifiers global company key (`gvkey`) and calendar year-quarter (`datacqtr`). Note that for variables that require a fiscal view, our dataset also has unique observations by the identifiers global company key (`gvkey`), fiscal year-quarter (`datafqtr`) and fiscal year-end month (`fyr`). Finally, we apply filters for currency code (`curcdq = USD`, `curncdq = USD`) and incorporation country code (`fic = USA`).

While we primarily rely on the quarterly dataset, we also use the annual dataset to obtain certain variables, such as employment, that are unavailable in the quarterly dataset. To ensure unique observations in the annual dataset, we apply the same screening variables. This approach yields unique observations by the identifiers global company key (`gvkey`), fiscal year (`fyear`) and fiscal year-end month (`fyr`). To merge the quarterly and annual dataset, we use the identifiers global company key (`gvkey`), fiscal year (`fyear`) and fiscal year-end month (`fyr`).

Climate change exposure and sentiment. We use the climate change exposure dataset developed by Sautner et al. (2023), accessed through OSF, to identify firm-level, quarterly climate change exposure and sentiment measures from earnings conference calls. To merge this dataset with the Compustat data, we rely on the identifiers global company key (`gvkey`), calendar year-quarter (`datacqtr`), and 6-digit CUSIP (company/issuer identifier).

Two key points are worth noting. First, we use the 6-digit CUSIP as an additional identifier in the merge because the global company key (`gvkey`) and calendar year–quarter (`datacqtr`) do not jointly uniquely identify observations. We use the 6-digit CUSIP rather than the standard 9-digit CUSIP to increase matches at the issuing-company level. Finally, we allow firms to be headquartered globally, not only in the United States.

BEA fixed assets data. We use the BEA Fixed Assets Accounts Table (Section 3: Private Fixed Assets by Industry) to obtain annual, sector-level depreciation rates. Fixed assets consist of three components—private equipment, structures, and intellectual property products—each with distinct depreciation rates. Following Ottonello and Winberry (2020), for each sector we compute component-specific depreciation rates by dividing the current-cost depreciation of each fixed asset component by the current-cost net stock of the corresponding component. We then construct a sectoral depreciation rate as a weighted average of the component-specific rates, using each component's net stock share as weights. Finally, we convert the annual depreciation rate to a quarterly rate, assuming equal compounding across the four quarters.

While the BEA publishes implied depreciation rates, these are not available at the NAICS 2-digit (sector) level, which is the level of NAICS aggregation available for several firms in the Compustat dataset. We therefore implement the above procedure to construct depreciation rates at the NAICS 2-digit level.

Table C.2: Micro data: Description

Variable name	Variable codes	Calculations and notes
Acquisition ratio	aqc: Acquisitions, year-to-date atq: Assets, total	Δ aqc / atq
Capital	ppegtq: Property, plant, and equipment (gross) ppentq: Property, plant, and equipment (net) δ: Depreciation rate (computed from BEA data)	We calculate the end-of-period capital using the perpetual inventory method, following Ottonello and Winberry (2020).
Investment	capxy: Capital expenditures, year-to-date	We linearly interpolate missing values within a firm for a given fiscal year and fiscal year-end month. Next, we difference within the firm to obtain quarterly capital expenditures.
Investment ratio	capxyq: Capital expenditures year-to-date, interpolated and differenced ppentq: Property, plant, and equipment (net)	capxyq / L.ppentq
Climate change exposure	cc_expo_ew: Climate change exposure measure from Sautner et al. (2023)	
Climate change sentiment	cc_sent_ew: Climate change sentiment measure from Sautner et al. (2023)	
Employees	emp: Employees	
Liquidity ratio	cheq: Cash and short-term investments atq: Assets, total	cheq / atq
Leverage ratio	dlcq: Debt in current liabilities dlttq: Long-term debt, total atq: Assets, total	$(\texttt{dlcq} + \texttt{dlttq})/\texttt{atq}$
Sales	saleq: Sales/turnover (net)	
TFP	saley: Sales/turnover (net), year-to-date capital: Capital, as computed above emp: Employees	Residual of the following equation, estimated by sector: $\log \texttt{saley}_{it} = \mu_i + \delta_t + \alpha_s^k \log \texttt{capital}_{it} + \alpha_s^n \log \texttt{emp}_{it} + \varepsilon_{it}$, where s represents the sector.
Research and development expense	xrdq: Research and development expense	

Sample restrictions. To align with the sample period used for the VAR estimation, we set the firm-level analysis sample to span the period 1986 to 2019. Subsequently, we exclude firms within the finance, insurance, and real estate sectors (SIC codes: 6000–6799) as well as those in the public administration sectors (SIC codes: 9100–9799). Next, we impose the following set of sample restrictions on firm-quarter observations by year, following Cloyne et al. (2023). Specifically, we apply restrictions based on the annual distribution of firm-quarter observations. Note that we do not impose these restrictions sequentially and we do not impose these restrictions on missing observations.

- We drop firm-quarter observations with capital expenditures ratio in the top and bottom 1%.
- We drop firm-quarter observations with liquidity ratio greater than 1.
- We drop firm-quarter observations with leverage ratio in the top 1%.
- We drop firm-quarter observations with real sales growth in the top and bottom 1%.
- We drop firm-quarter observations where the absolute value of the acquisitions-to-assets ratio is greater than 5%.
- We drop firms which are in the panel for less than 20 quarters.

Deflator series. The deflator series is defined as the chain-type price index for gross value added (GDP) by non-farm business, which we obtain from FRED.

D. Additional results

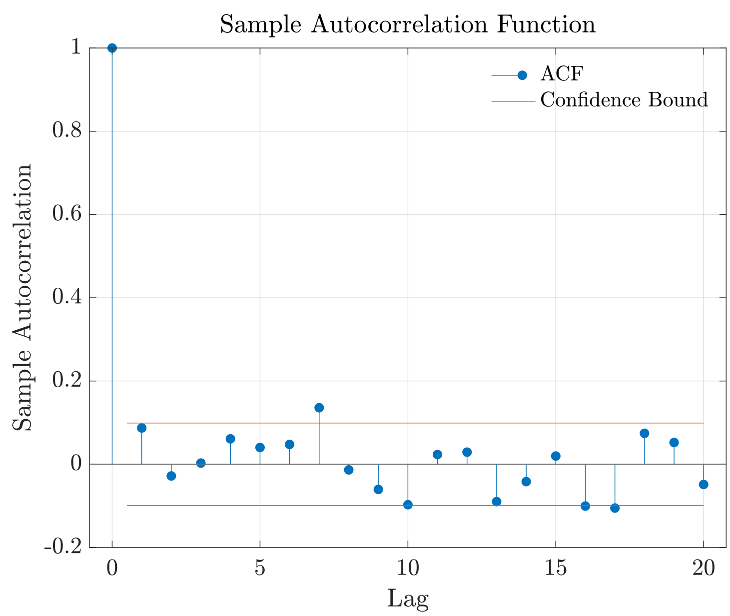
In this appendix, we present some diagnostics on the instrument and additional results discussed in the main text.

D.1. Diagnostics of the instrument

As discussed in the paper, we perform a number of additional validity checks on the climate policy uncertainty instrument. In this section, we investigate the autocorrelation and forecastability of the instrument, as well as its correlation with shocks from the literature.

Autocorrelation. In Figure D.1, we present the autocorrelation function. As discussed in the main text, climate policy uncertainty events are concentrated in the late 2000s and from mid-2010 onwards, which leads to the series being weakly serially correlated. However, our results are robust to using a residualized version of the instrument purged from autocorrelation, see Appendix Figure D.4.

Figure D.1: Autocorrelation Function



Forecastability. In Table D.1, we present the results of a number of Granger causality tests. We find little evidence that macroeconomic or financial variables have any power in forecasting the instrument. For all variables considered, the p-values for the Granger causality test are far above conventional significance levels, with the joint test having a p-value of 0.95.

Table D.1: Granger causality tests

Variable	**p-value**
Instrument	0.1191
Climate policy uncertainty	0.7881
Industrial production	0.5294
Unemployment rate	0.7117
Commodity prices	0.1946
PPI	0.9390
CPI	0.7291
Policy rate	0.9874
Climate policy news	0.9118
Climate policy sentiment	0.9980
Economic policy uncertainty	0.4363
Trade policy uncertainty	0.7953
Geopolitical risk	0.6969
VXO	0.2083
Joint	0.9470

Notes: This table shows the p-values from a series of Granger causality tests of the climate policy uncertainty instrument across a selection of macroeconomic and financial variables. To be able to conduct standard inference, the series are made stationary by taking first differences where necessary. The lag order is set to 12 and in terms of deterministics, only a constant term is included.

Correlation with other shocks. Finally, in Table D.2 we examine how the instrument correlated with other shocks from the literature. The instrument is uncorrelated with other structural shock measures from the literature, including uncertainty, oil, productivity, news, monetary policy, fiscal policy, and financial shocks.

Table D.2: Correlation with other shock measures

Shock	Source	ρ	p-value	n	Sample
Panel A: Uncertainty shocks					
Uncertainty	Bloom, 2009	-0.04	0.48	384	1986M01-2017M12
	Baker, Bloom, and Davis, 2016	0.03	0.54	384	1986M01-2017M12
	Piffer and Podstawski, 2017	-0.02	0.68	355	1986M01-2015M07
Panel B: Oil shocks					
Oil price	Hamilton, 2003	-0.06	0.23	384	1986M01-2017M12
Oil supply	Kilian, 2008	0.04	0.58	225	1986M01-2004M09
	Caldara, Cavallo, and Iacoviello, 2019	0.04	0.48	360	1986M01-2015M12
	Baumeister and Hamilton, 2019	-0.02	0.74	408	1986M01-2019M12
	Kilian, 2009	0.04	0.49	264	1986M01-2007M12
Global demand	Kilian, 2009	-0.07	0.25	264	1986M01-2007M12
Oil-specific demand	Kilian, 2009	0.03	0.63	264	1986M01-2007M12
Oil supply news	Känzig, 2021	0.03	0.53	408	1986M01-2019M12
Panel C: Productivity and news shocks					
Productivity	Basu, Fernald, and Kimball, 2006	-0.03	0.77	104	1986Q1-2011Q4
	Smets and Wouters, 2007	0.10	0.40	76	1986Q1-2004Q4
News	Barsky and Sims, 2011	0.16	0.13	87	1986Q1-2007Q3
	Kurmann and Otrok, 2013	0.14	0.21	78	1986Q1-2005Q2
	Beaudry and Portier, 2014	-0.08	0.42	107	1986Q1-2012Q3
Panel D: Monetary policy					
Monetary policy	Romer and Romer, 2004	0.04	0.66	132	1986M01-1996M12
	Gertler and Karadi, 2015	-0.04	0.50	324	1990M01-2016M12
	Miranda-Agrippino and Ricco, 2021	0.08	0.23	228	1991M01-2009M12
	Bauer and Swanson, 2023	0.04	0.48	383	1988M02-2019M12
	Aruoba and Drechsel, 2024	-0.01	0.81	274	1986M01-2008M10
Panel F: Fiscal policy shocks					
Fiscal policy	Romer and Romer, 2010	-0.04	0.68	88	1986Q1-2007Q4
	Fisher and Peters, 2010	0.00	0.98	92	1986Q1-2008Q4
	Ramey, 2011	-0.07	0.48	100	1986Q1-2010Q4
Panel F: Financial shocks					
EBP	Gilchrist and Zakrajšek, 2012	-0.04	0.46	360	1986M01-2015M12
Loan supply	Bassett et al., 2014	0.03	0.78	76	1992Q1-2010Q4

Notes: This table shows the correlation of the climate policy uncertainty instrument with a wide range of structural shock measures from the literature. ρ is the Pearson correlation coefficient, the p-value corresponds to the test whether the correlation is different from zero, and n is the sample size. When the shock measure is only available at the quarterly frequency, the instrument is aggregated by summing across months.

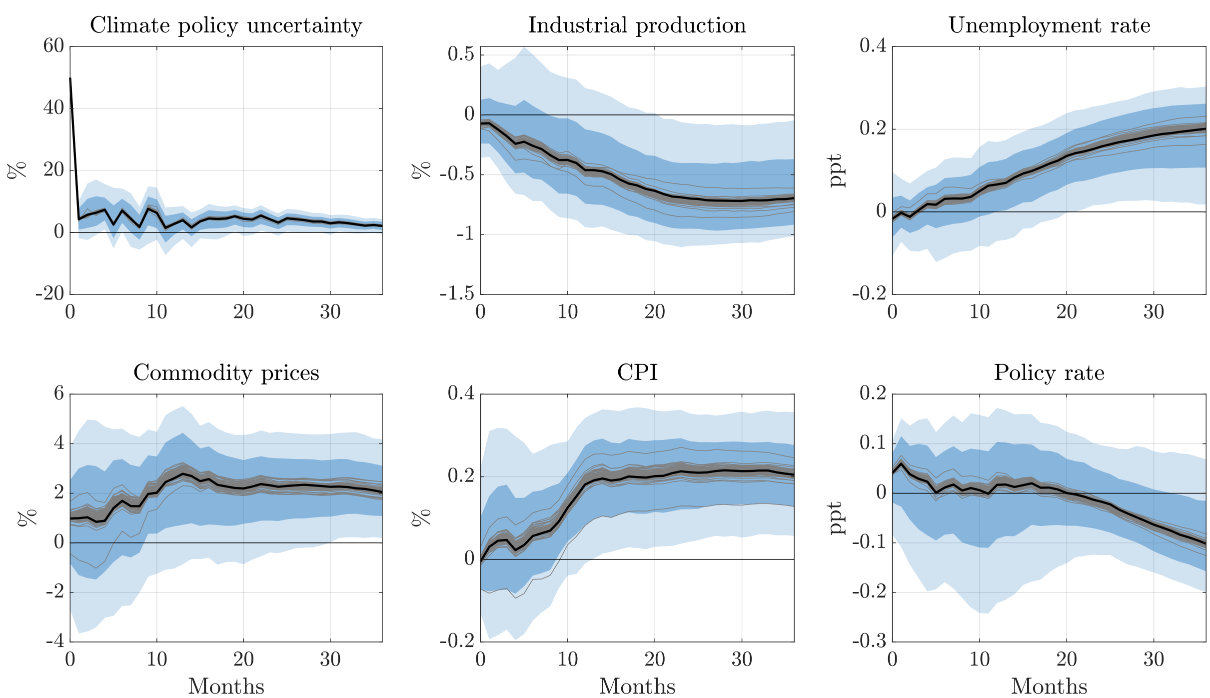
D.2. Additional analyses and sensitivity

In this section, we perform a number of robustness checks on the identification strategy and empirical specification.

D.2.1. Instrument construction.

Jackknife exercise. We perform a jackknife exercise to analyze whether our results are disproportionately driven by any individual event. Specifically, the procedure involves censoring each observation in our climate policy uncertainty event series to zero and re-estimating the external instruments VAR using this modified instrument. Figure D.2 shows the collection of responses using the modified instrument (in gray), along with the baseline response (in black). The results do not appear to be driven by any individual event, as the resulting responses lie safely within the 68 percent confidence interval of the baseline model.

Figure D.2: Sensitivity with respect to individual events



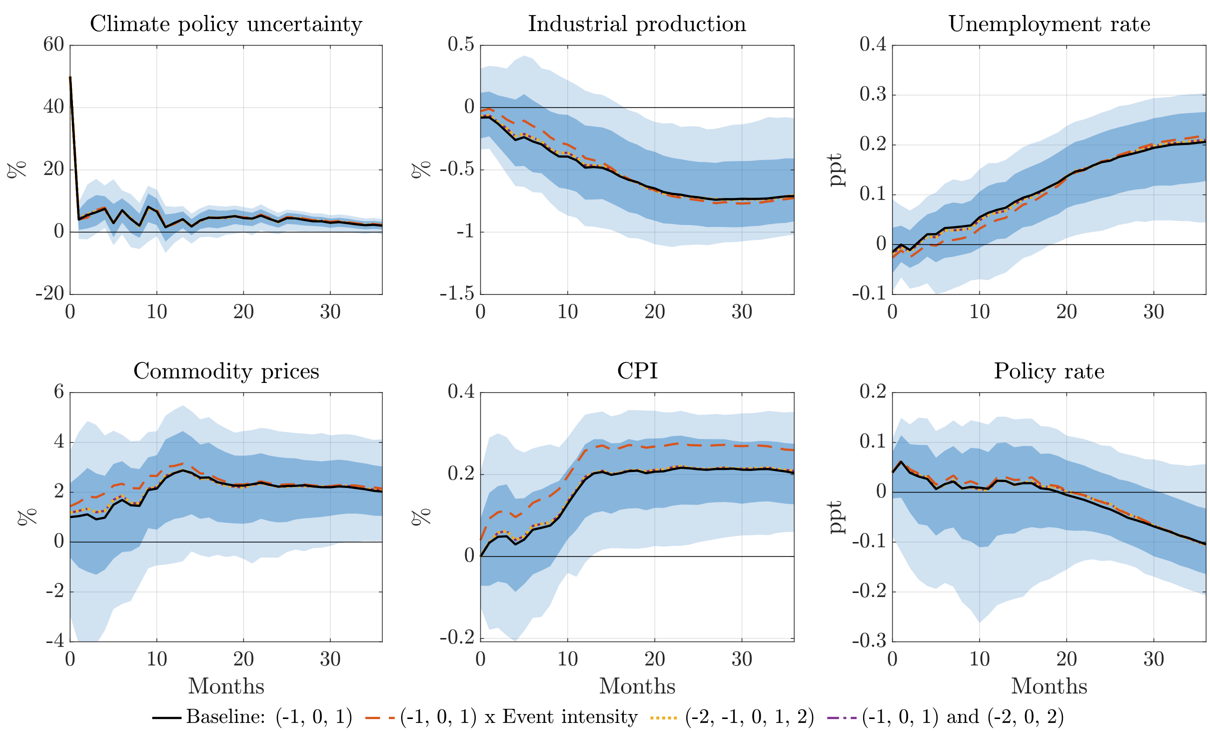
Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR, censoring each observation in our climate policy uncertainty event series to zero at a time (solid gray lines). The black line is the point estimate and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

Controlling for stringency. Recall that our baseline stringency index, "(-1, 0, 1) index", is constructed to capture the direction of policy news for each event in our climate policy uncertainty event series.

To assess the sensitivity of our results to the construction of the stringency index, we construct three alternative indices that aim to additionally capture the magnitude of policy news. First, we construct an index assuming that magnitude scales linearly with event reporting intensity ("(-1, 0, 1) $\times$ event intensity index"). Second, we create a refined stringency index where we assign larger magnitudes (+2 or -2) to decisive or binding policy actions and smaller values (+1 or -1) to developments earlier in the policy cycle ("(-2, -1, 0, 1, 2) index"). Finally, we consider a variant that allows for decisive or binding policy actions to have effects larger than ± 1 ("(-1, 0, 1) and (-2, 0, 2) index").

The results are shown in Figure D.3, with the results being virtually identical whether we control for the direction of policy news, or for both the direction and magnitude of policy news.

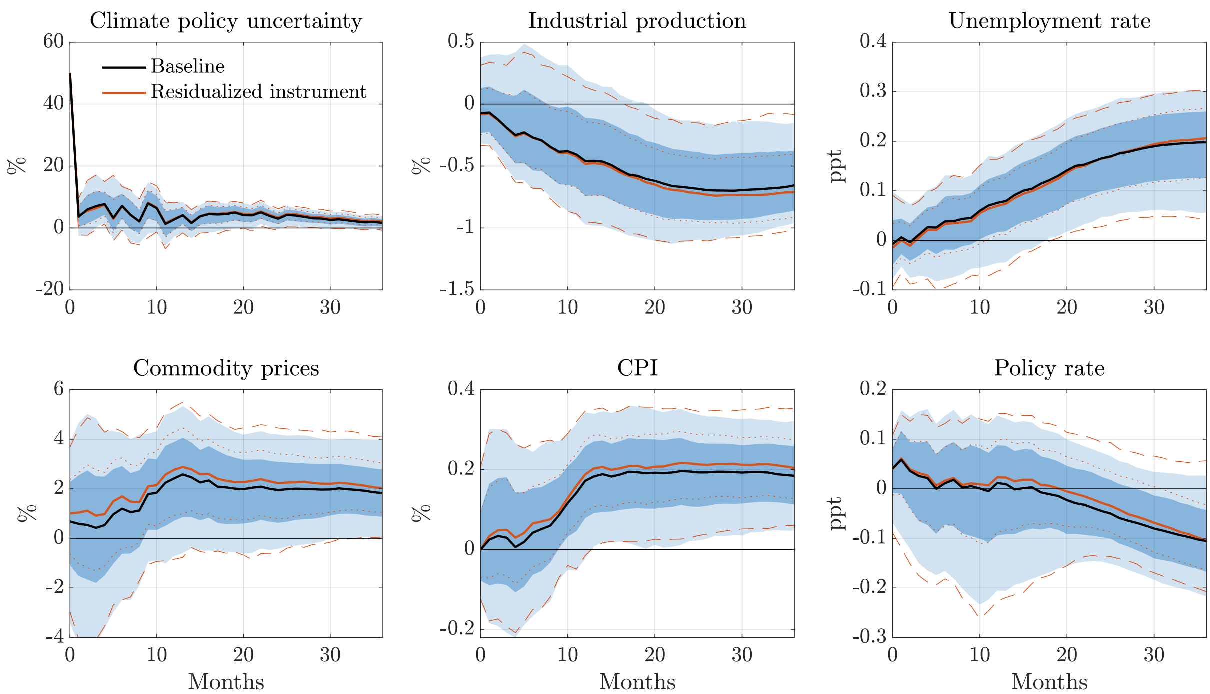
Figure D.3: Sensitivity with respect to the stringency index



Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR using different stringency indices: (-1, 1) index (baseline), (-1, 1) index $\times$ event intensity (orange), (-2, -1, 0, 1, 2) index (yellow), and (-1, 0, 1) and (-2, 0, 2) index (purple). The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

Residualizing the instrument. Figure D.4 displays the results using a resdiualized version of our baseline instrument, where we purge the autocorrelation in the instrument using 12 lags, following Miranda-Agrippino and Ricco (2021). The responses using the resdiualized instrument are identical to our baseline instrument, suggesting that autocorrelation in the instrument does not appear to be of concern in our application.

Figure D.4: Sensitivity with respect to autocorrelation in instrument



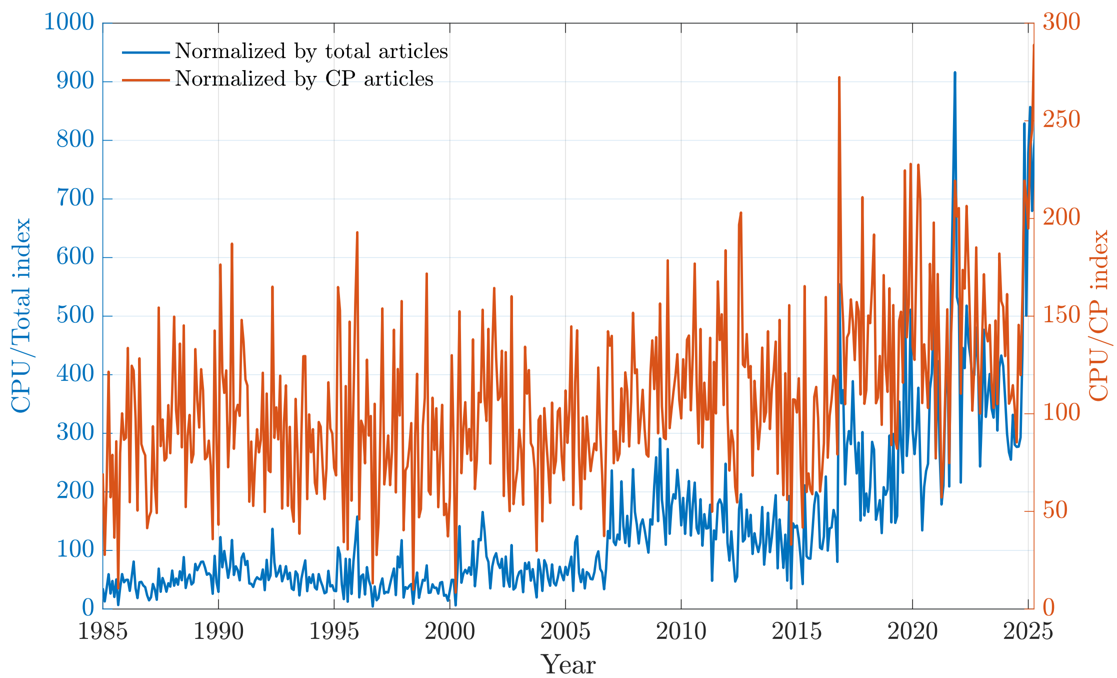
Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR compared to a model using a residualized version of our baseline instrument. The solid lines are point estimates and the dark (dotted) and light (dashed) shaded areas (lines) are 68 and 90 percent confidence bands, respectively.

D.2.2. Normalization of index

In this section, we explore the sensitivity of our results with respect to the normalization of the climate policy uncertainty (CPU) index. As outlined in Section A.2.2, we first normalize the number of articles on climate policy uncertainty by the total number of articles published in the same newspaper and over the same month, and then standardize the resulting series and average across all newspapers to obtain the CPU index.

An alternative approach instead is to normalize the number of articles on climate policy uncertainty by the total number of *climate policy* (CP) articles published in the same newspaper and over the same month. Figure D.5 plots the resulting alternative index alongside our baseline CPU index. The two series track each other closely, with a correlation of 0.73 over our sample. The increase in climate policy uncertainty is more pronounced in the index normalized by the total number of articles, likely reflecting the fact that climate change has become a more salient topic over time. However, our identification strategy exploits spikes in the index around events that generated uncertainty about climate policy, rather than the gradual increase in the index over time.

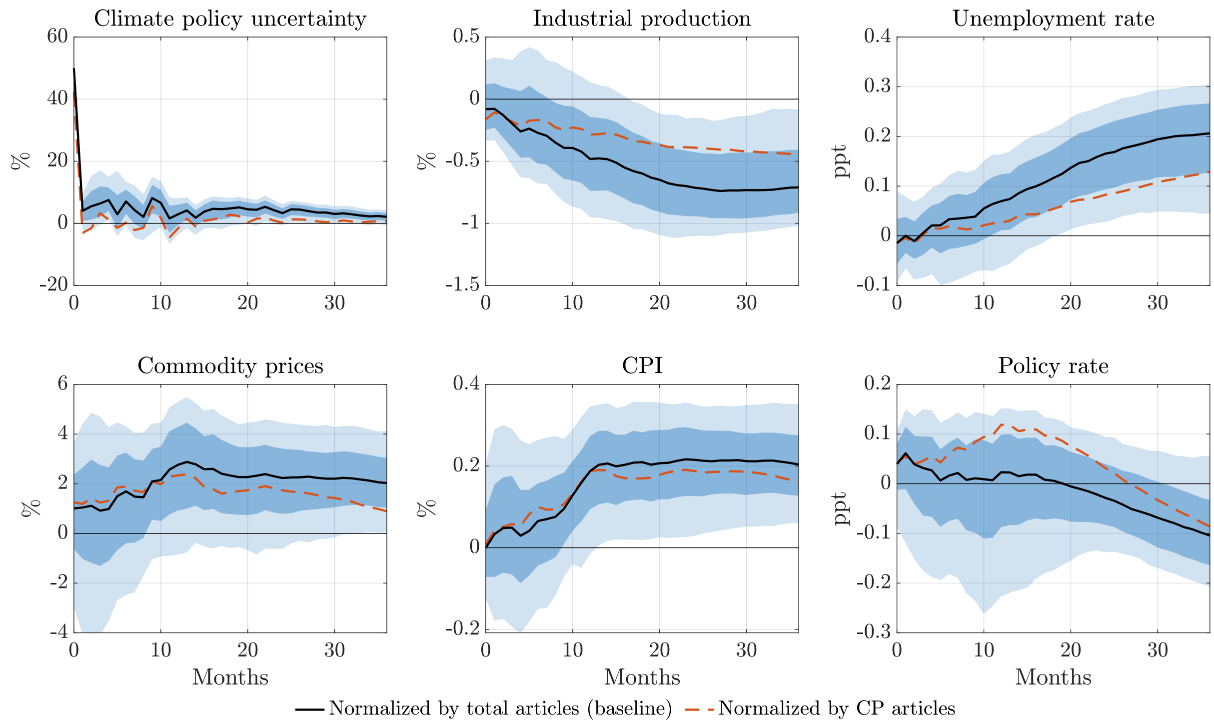
Figure D.5: Climate policy uncertainty index: Alternative normalization



Notes: Climate policy uncertainty indices based on newspaper coverage in the *New York Times*, the *Wall Street Journal*, the *Washington Post*, and the *Los Angeles Times*, normalized by total articles (blue) and climate policy articles (orange).

Figure D.6 presents the impulse responses obtained using both CPU indices: the baseline index normalized by total articles and the alternative index normalized by climate policy articles (orange). In line with the intuition discussed above, the resulting impulse responses are very similar across the two measures, indicating that our results are not driven by the choice of normalization.

Figure D.6: Sensitivity with respect to normalization



Notes: Impulse responses a climate policy uncertainty shock, estimated using our baseline external instruments VAR using different CPU measures: the CPU index normalized by total articles (baseline) and the CPU index normalized by climate policy articles (orange). The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

D.2.3. LLM vs. dictionary-based index

In Appendix A.2.3, we leverage LLMs to validate our baseline index. As a complementary exercise, we also construct a CPU index directly using LLM-based classification following Iacoviello and Tong (2026). Specifically, we use an LLM to identify articles that discuss climate policy and explicitly reference uncertainty about such policies. This is a natural application for LLMs, as they are well suited to capturing contextual and semantic nuances—allowing them to distinguish between general discussions of climate policy and articles that genuinely reflect uncertainty about policy direction, implementation, or effects.

Construction. To construct an LLM-based CPU index, we use the `gpt-4o-mini` model, accessed through the *OpenAI API*, to classify whether each article in our sample discusses uncertainty regarding climate policy. As the exercise requires access to full article texts, we rely on articles from the *Wall Street Journal* and the *Washington Post*, accessed through the *Factiva API*.

We first identify a subset of articles that discuss climate policy *news*. An article is included in this set if it contains concepts from the predefined *narrow* dictionaries according to the following criteria:

(Climate change dictionary **AND** Policy dictionary)
OR Climate policy dictionary

Next, we apply the LLM classifier to this full sample (59,326 articles) to identify those that additionally discuss uncertainty about climate policy. We feed the full text of each article individually into the model to limit hallucination, keep the temperature parameter low to ensure focused and deterministic responses, and instruct the model to provide a brief explanation of its classification to facilitate human validation. The prompt we feed in is as follows:

> "I'm providing an article that discusses policy measures related to climate change. The article does not need to focus primarily on climate policy; it is sufficient if the topic appears in some paragraphs.
>
> Your task is to determine whether the article discusses uncertainty, risk, or ambiguity about the climate policy.
>
> Return your response as a JSON object in the following format:
>
> `{"classification": <number>,`

```
"explanation": <"brief explanation (1-2 sentences)">}
```

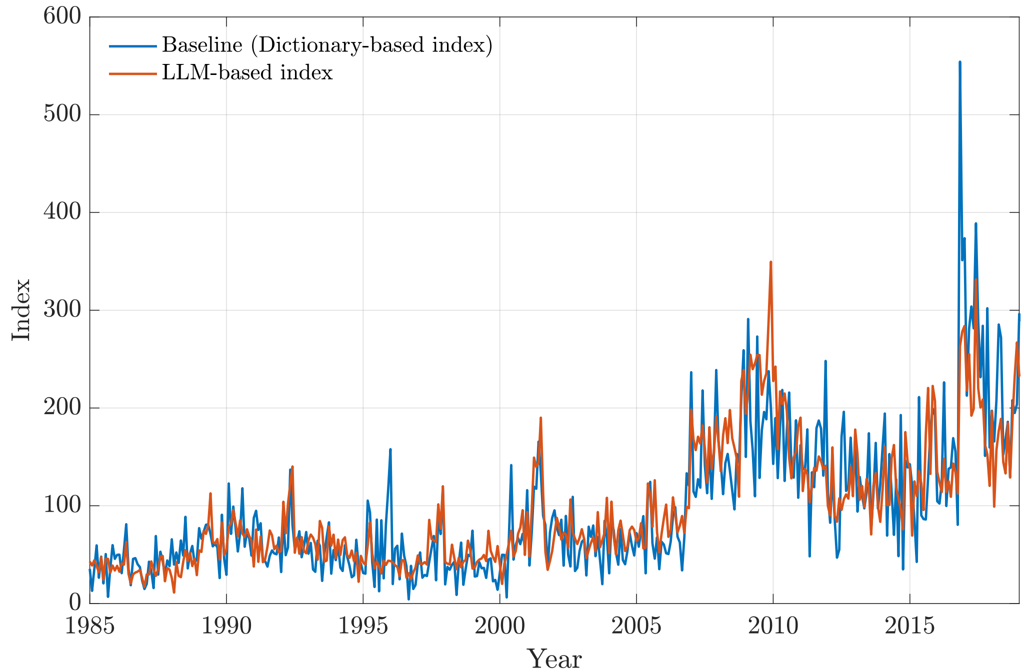
Classification values:

- 1 = Yes (the article discusses uncertainty about climate policy);
- 0 = No (the article does not discuss uncertainty about climate policy);
- 99 = Unsure.

Ensure the output is a valid JSON object with no extra text."

LLM-based index. We construct the LLM-based CPU index following the same procedure as our baseline measure, as outlined in Section A.2.2. Specifically, we scale the number of LLM-classified uncertainty articles by the total number of articles published in the same newspaper and over the same month, standardize the resulting series for each newspaper, and average across the newspapers. Figure D.7 plots the LLM-based index alongside our baseline dictionary-based CPU index. The two series track each other closely over our sample period, with a correlation of 0.84, suggesting that the LLM classifier and dictionary-based approach capture similar variation in climate policy uncertainty. Both indices exhibit comparable spikes around key episodes of elevated uncertainty, lending further credibility to our dictionary-based approach.

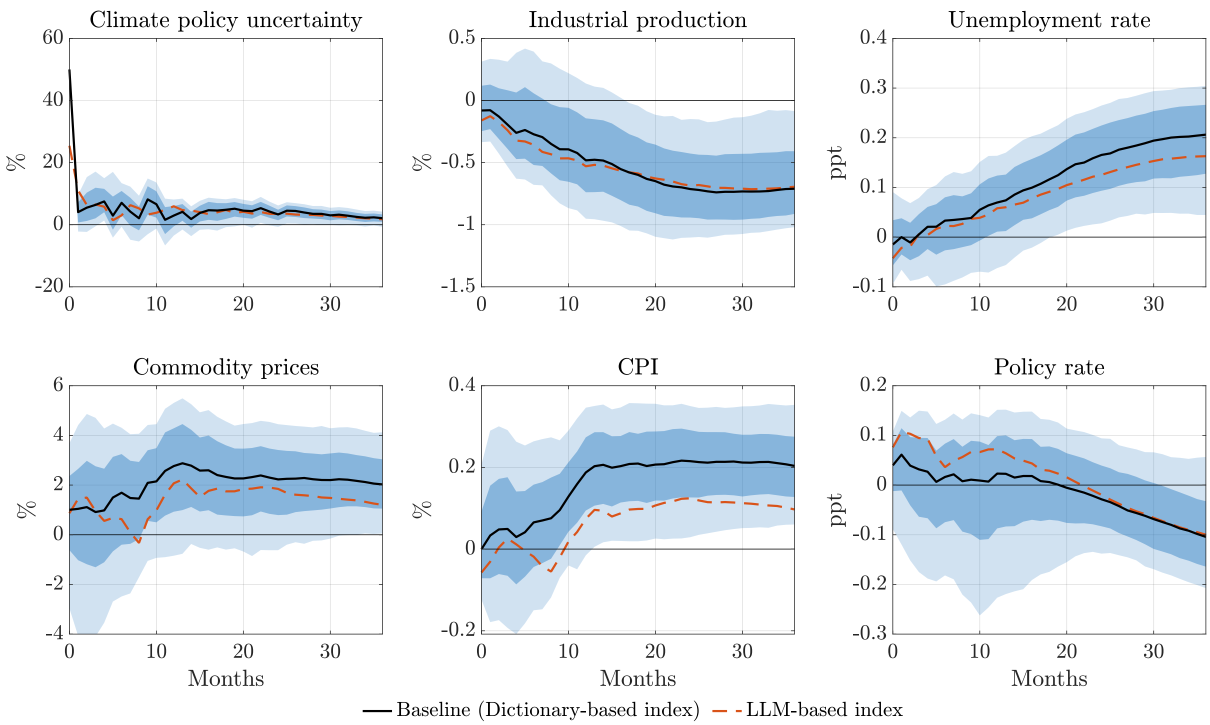
Figure D.7: Climate policy uncertainty index: Dictionary vs. LLM-based approach



Notes: Climate policy uncertainty indices, constructed using the dictionary-based approach (blue) and LLM-based approach (orange).

Results. Figure D.8 presents the impulse responses obtained using both CPU indices: the baseline dictionary-based index and the alternative LLM-based index. The resulting impulse responses are very similar across the two measures, indicating that our results are not driven by the choice of index construction method. This finding reinforces the validity of our baseline approach and demonstrates that the narrow dictionary along with the uncertainty terms reliably capture variation in climate policy uncertainty that is relevant for our identification strategy.

Figure D.8: Sensitivity with respect to index construction

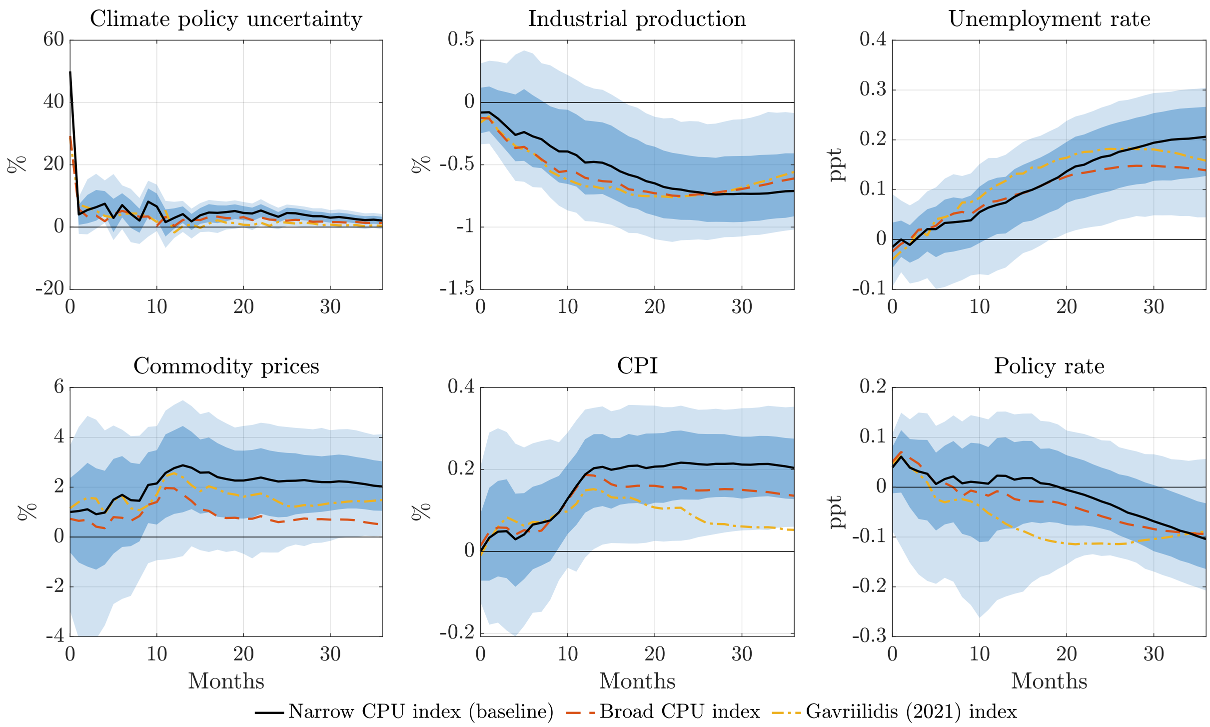


Notes: Impulse responses a climate policy uncertainty shock, estimated using our baseline external instruments VAR using different CPU measures: the CPU index constructed using the dictionary-based approach (baseline) and the CPU index constructed using the LLM-based approach (orange). The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

D.2.4. Construction of the CPU index

Figure D.9 presents the impulse responses using a selection of different CPU indices: our narrow CPU index (baseline), our broad CPU index (orange), and the original index in Gavriilidis (2021) (yellow).

Figure D.9: Impulse responses based on alternative CPU measures

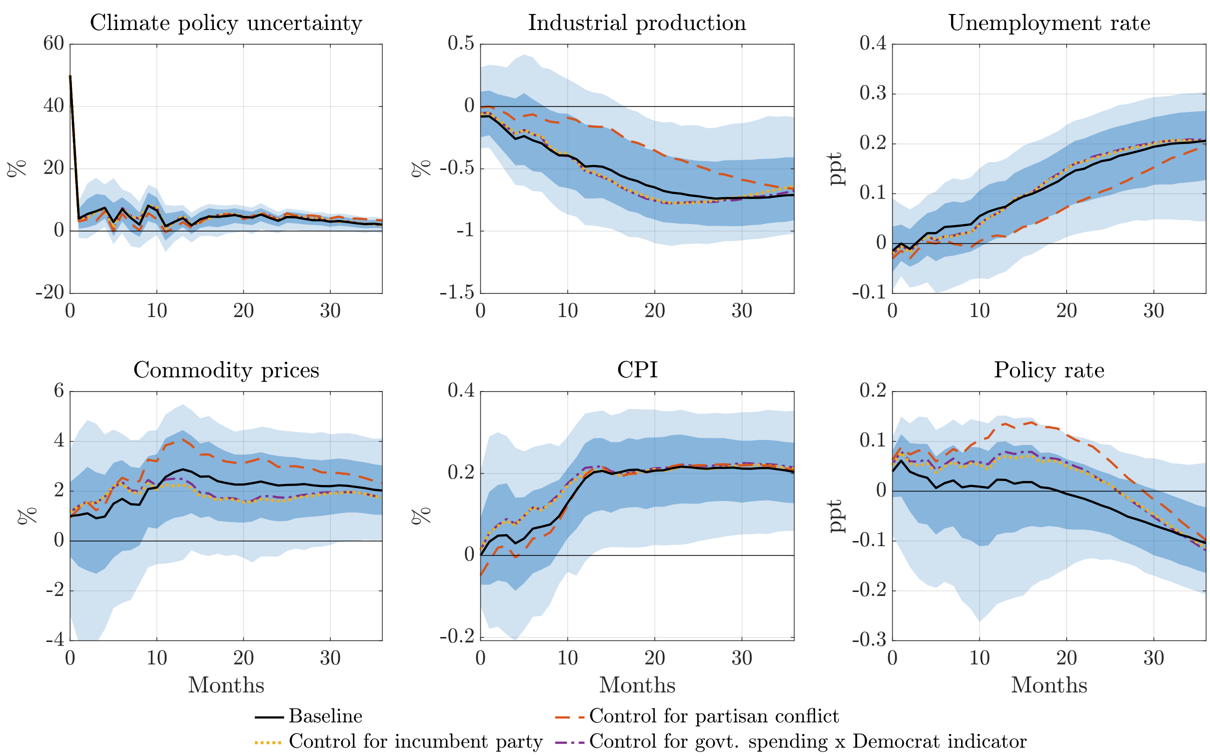


Notes: Impulse responses to a one standard deviation climate policy uncertainty shock, estimated using our baseline external instruments VAR using different CPU measures: our narrow CPU index (baseline), our broad CPU index (orange), and the original index in Gavriilidis (2021) (yellow). The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

D.2.5. Additional controls

Controlling for political factors. Figure D.10 shows the impulse responses in a model where we control for partisan conflict (orange) and the incumbent party in the federal administration (yellow). The responses appear to be robust to controlling for political factors, suggesting that we are capturing changes in climate policy uncertainty orthogonal to broader changes in the political landscape. To control for countercyclical green fiscal policy episodes specifically, such as those associated with the American Recovery and Reinvestment Act, we further include government spending interacted with a Democratic-administration indicator (purple). The results are again robust.

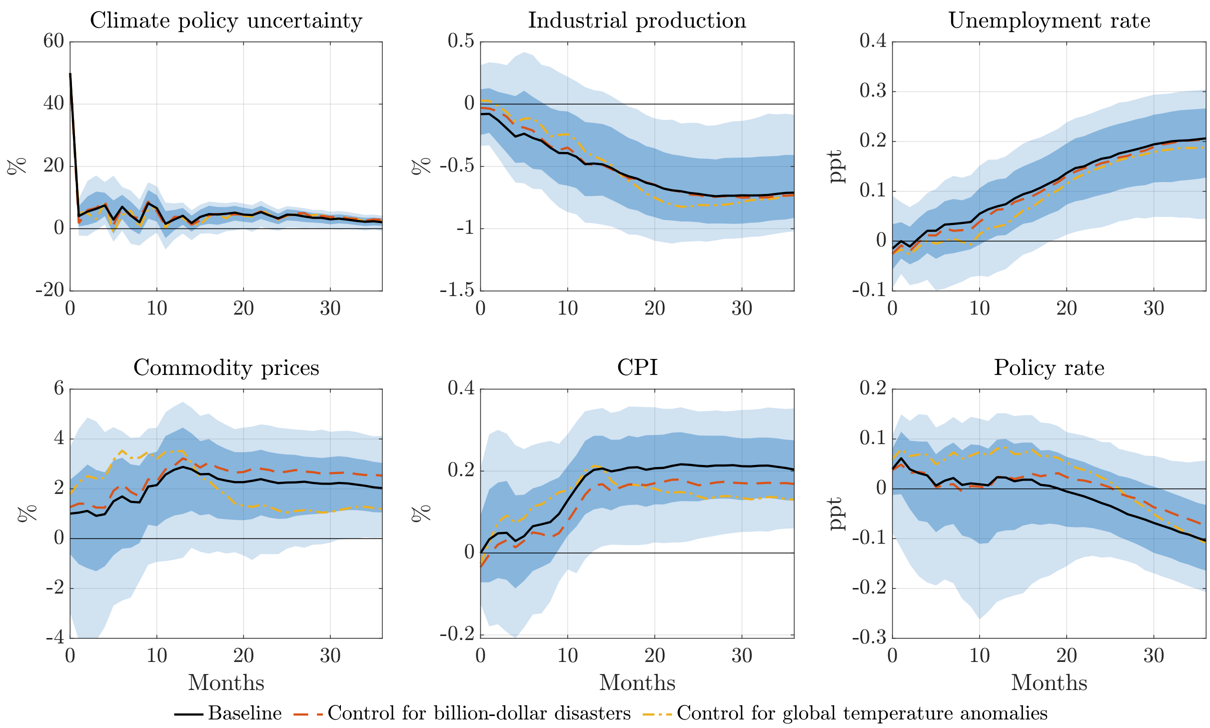
Figure D.10: Sensitivity with respect to political controls



Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR controlling for: partisan conflict (orange), incumbent party (yellow), and government spending interacted with a Democratic-administration indicator (purple). The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

Controlling for physical climate risks. Figure D.11 shows the impulse responses in a model where we control for the number of billion-dollar weather and climate disasters in the United States (orange) and global temperature anomalies (yellow). The responses are robust to controlling for physical climate risks, suggesting that we are capturing changes in climate policy uncertainty orthogonal to changes in physical climate risks.

Figure D.11: Sensitivity with respect to physical climate controls



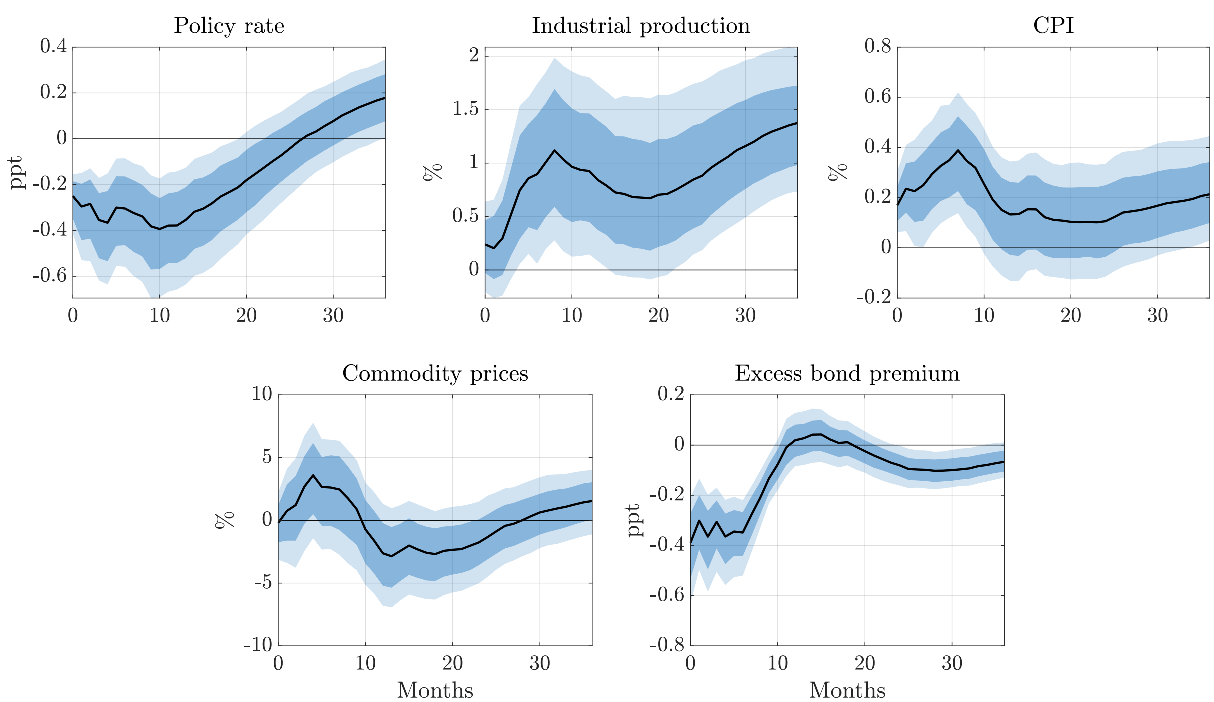
Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR controlling for: number of billion-dollar weather and climate disasters (orange) and global temperature anomalies (yellow). The lines are point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model.

D.2.6. Monetary policy VAR

We estimate the impulse responses to a monetary policy shock using a standard monetary VAR, close to our baseline VAR model. We replace the unemployment rate with the excess bond premium by Gilchrist and Zakrajšek (2012), which has been shown to be a crucial variable in monetary VARs. Furthermore, we exclude the climate policy uncertainty index. Otherwise, we replicate the empirical specification in our baseline model, using the same sample period (1985-2019), a lag length of 12, and including a constant and linear trend in terms of deterministics.

The results are shown in Figure D.12. As expected, an expansionary monetary policy shock leads to an increase in output and prices, and a fall in the excess bond premium. Qualitatively, the results are very similar to the estimated responses in Gertler and Karadi (2015) and Bauer and Swanson (2023). Quantitatively, the response of the policy rate turns out to be more persistent and consumer prices increase less persistently. These differences are driven by our shorter sample period.

Figure D.12: Impulse responses to a monetary policy shock

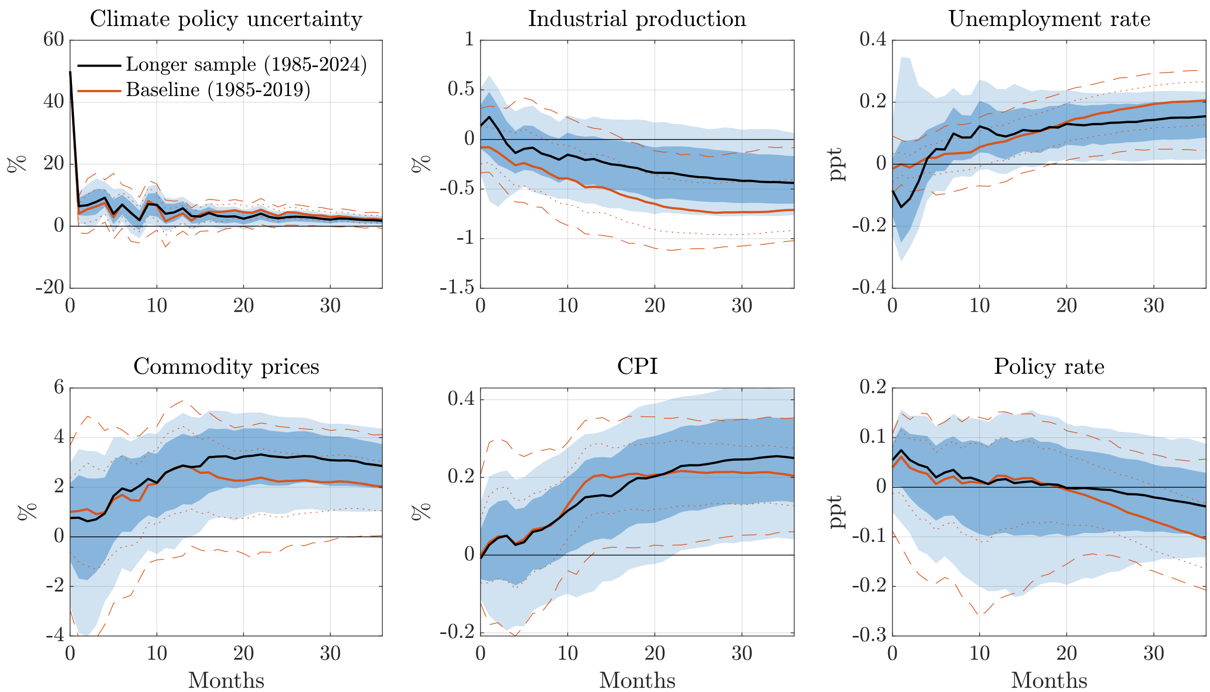


Notes: Impulse responses to a monetary policy shock, estimated using the purged high-frequency surprises from Bauer and Swanson (2023) as an external instrument in a monetary VAR model. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

D.2.7. Other VAR specification choices

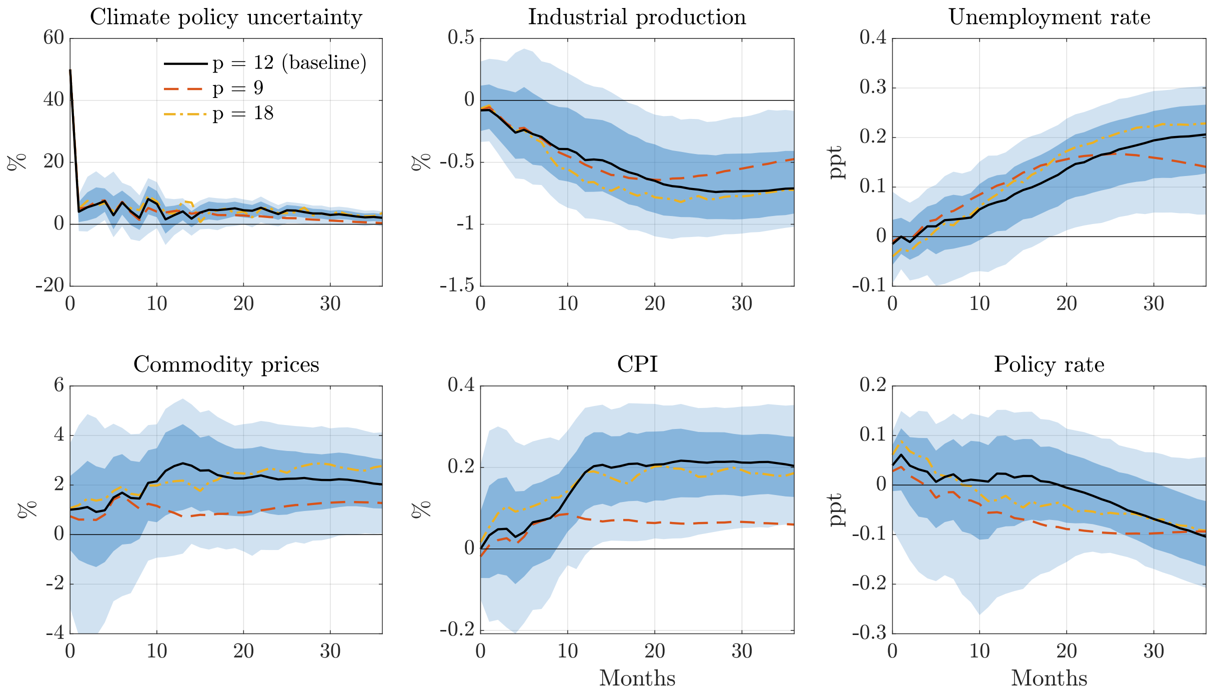
Figures D.13-D.15 show the results of the sensitivity checks with respect to additional specification choices, including the sample period, lag order, and deterministic variables. Our results turn out to be robust along all these dimensions.

Figure D.13: Sensitivity with respect to sample period



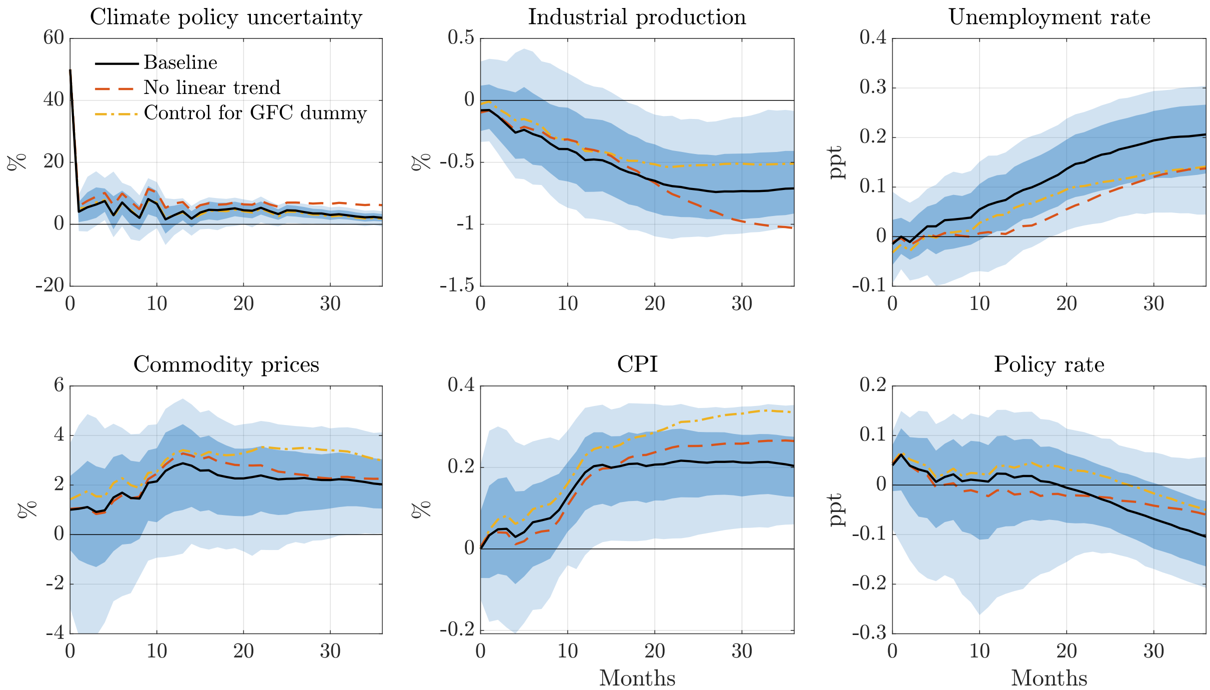
Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR compared to a model with a longer sample period (1985-2024). The lines are the point estimates and the dark (dotted) and light (dashed) shaded areas (lines) are 68 and 90 percent confidence bands, respectively.

Figure D.14: Sensitivity with respect to lag order



Notes: Impulse responses to a climate policy uncertainty shock, estimated using our external instruments VAR with varying lag order. The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands of our baseline model.

Figure D.15: Sensitivity with respect to deterministic variables

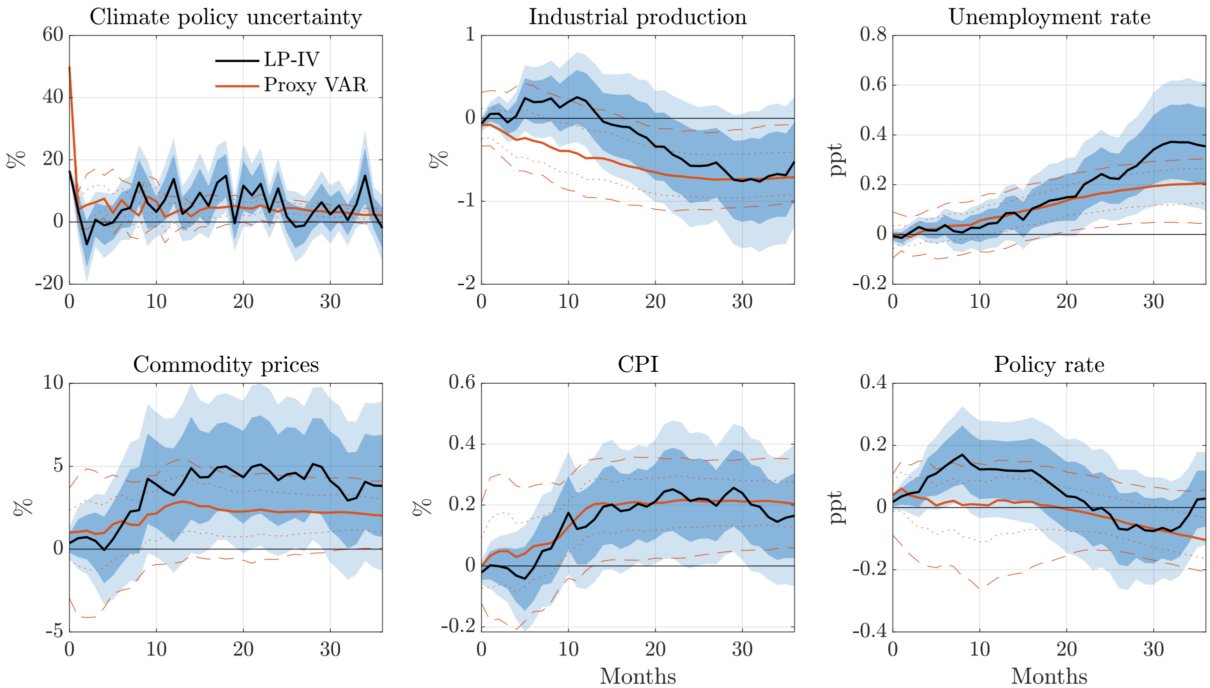


Notes: Impulse responses to a climate policy uncertainty shock, estimated using our baseline external instruments VAR compared to a model that excludes the linear trend (orange) and a model that controls for the global financial crisis using a dummy variable (yellow). The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands of our baseline model.

D.2.8. Estimation methodology

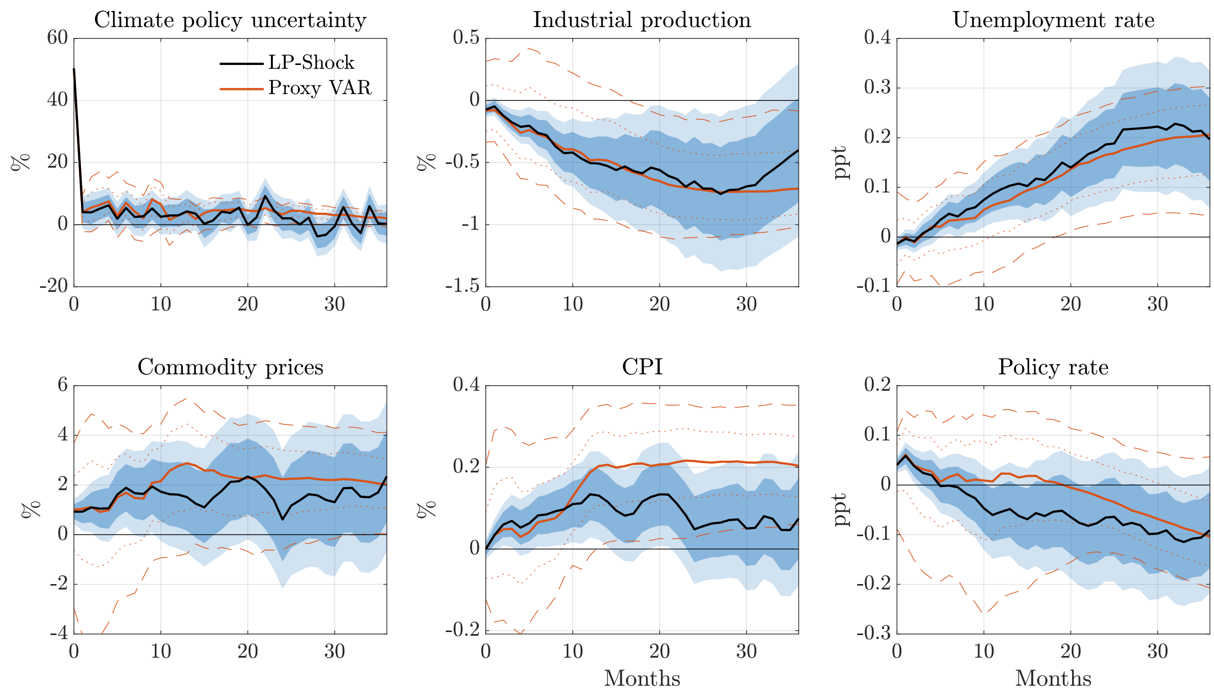
Local projections. Figures D.16-D.17 show the responses estimated based on local projection specifications, also reporting the estimated confidence bands.

Figure D.16: Impulse responses to a CPU shock, LP-IV



Notes: Impulse responses to a climate policy uncertainty shock, estimated using LP-IV. The lines are the point estimates and the dark (dotted) and light (dashed) shaded areas (lines) are 68 and 90 percent confidence bands, respectively.

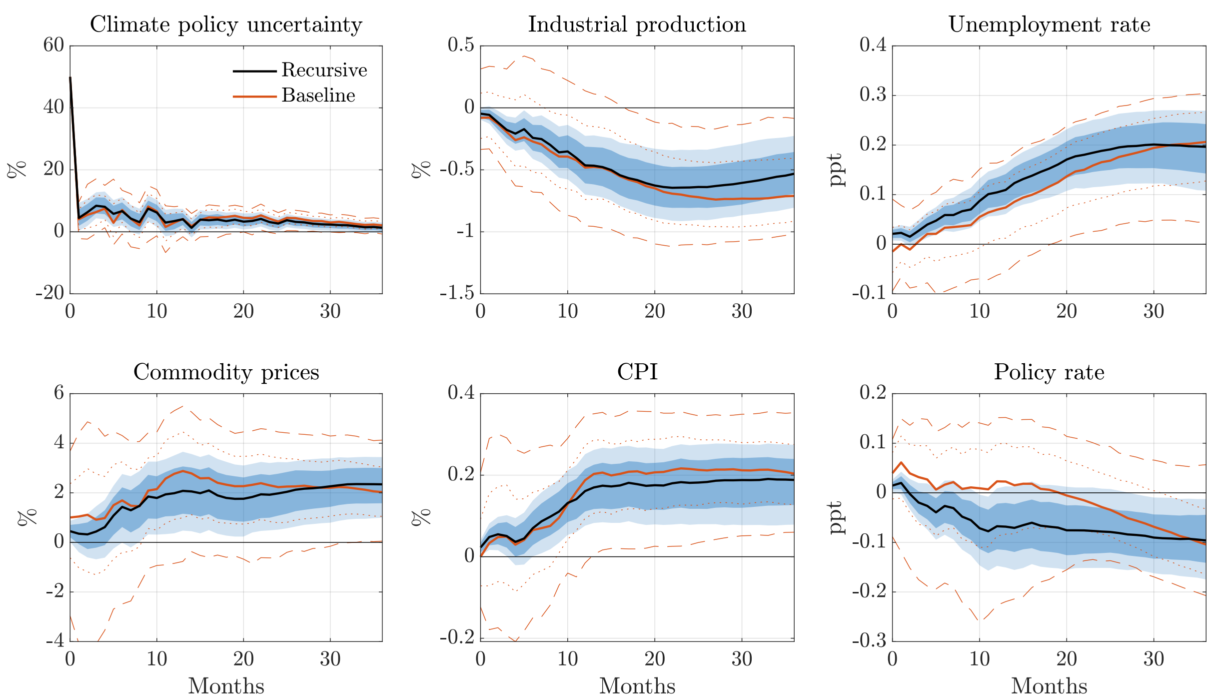
Figure D.17: Impulse responses to a CPU shock, LP on shock



Notes: Impulse responses to a climate policy uncertainty shock, estimated using LP on the VAR shock measure. The lines are the point estimates and the dark (dotted) and light (dashed) shaded areas (lines) are 68 and 90 percent confidence bands, respectively.

Recursive model. Finally, in Figure D.18 we report results from a VAR identified using short-run timing restrictions, a standard approach in the policy uncertainty literature. The approach assumes that climate policy uncertainty reacts to macroeconomic developments with a one month lag. Identifying a climate policy uncertainty shock in this way yields impulse responses that are pretty similar to those obtained from our baseline external-instrument VAR. Importantly, the two approaches rely on different sources of identifying variation. The instrumental-variable strategy exploits events that plausibly induced or resolved uncertainty, controlling for changes in expected policy stringency, whereas the recursive VAR identifies shocks directly from the climate policy uncertainty index under short-run timing restrictions. The close correspondence between the resulting impulse responses therefore lends further credibility to the identified climate policy uncertainty shock. As expected, the recursive VAR delivers tighter confidence bands, reflecting the stronger identifying assumptions it imposes.

Figure D.18: Impulse responses to a CPU shock, recursive VAR

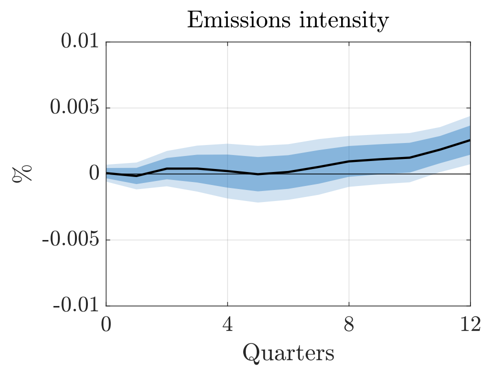


Notes: Impulse responses to a climate policy uncertainty shock, normalized to increase the CPU index by 50 percent on impact, estimated using the VAR identified with short-run zero restrictions. The lines are the point estimates and the dark (dotted) and light (dashed) shaded areas (lines) are 68 and 90 percent confidence bands, respectively.

D.2.9. Additional aggregate results

Emissions intensity. Figure D.19 presents the aggregate response of emissions intensity to a climate policy uncertainty shock. Emissions intensity, defined as the ratio of CO2 emissions relative to GDP, does not respond significantly to climate policy uncertainty—if anything it increases slightly. This reinforces the interpretation that the observed decline in emissions is driven by reductions in output, as opposed to improvements in emissions intensity.

Figure D.19: Impact on emissions intensity

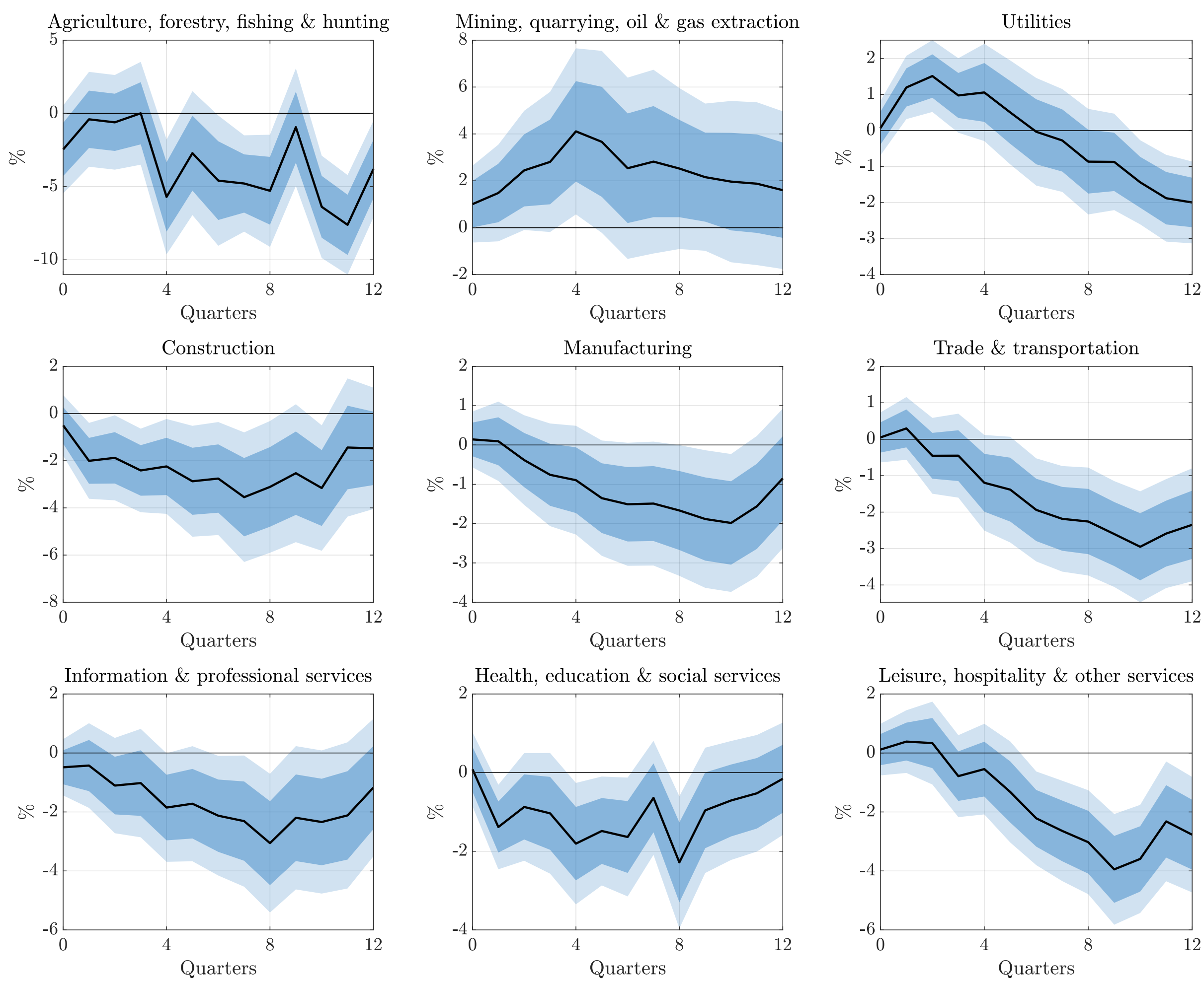


Notes: Impulse response of emissions intensity to a climate policy uncertainty shock, estimated using local projections (7) on the aggregated climate policy uncertainty shock extracted from our baseline external instruments VAR. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

D.2.10. Additional firm-level results

Sectoral heterogeneity. Figure D.20 presents the average investment response to climate policy uncertainty across a detailed set of sectors. While the responses are broadly similar across most sectors and generally indicate a decline in investment, the mining, quarrying, oil and gas extraction, and utilities sectors stand out by exhibiting a positive investment response, at least in the short run.

Figure D.20: Heterogeneous effects based on sector



Notes: Heterogeneous response of investment and R&D expenses to a climate policy uncertainty shock by sector, estimated using sector-specific panel local projections (10) on the aggregated climate policy uncertainty shock. The black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

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