The Macroeconomic Effects of Climate Policy Uncertainty*

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Abstract

We develop a novel 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 an 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. Monetary policy counteracts these inflationary pressures, affecting the transmission of climate policy uncertainty. Firm-level analyses show stronger declines in investment and R&D when firms have higher climate change exposure.

JEL classification: D80, E66, H23, L50, Q58

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1. Introduction

The accelerating impacts of climate change pose unprecedented risks to global ecosystems, economic stability, and social wellbeing. While governments around the world have begun to implement policies to confront this challenge, the future direction of climate policy remains highly uncertain. This uncertainty has intensified since Donald Trump's 2024 re-election, given his intention to dramatically reshape U.S. climate policy. A key concern among policymakers worldwide is the economic cost of the climate transition. However, uncertainty about climate policy can itself generate adverse economic effects, potentially outweighing the short-term costs of decarbonization. Despite its significance, the macroeconomic consequences of uncertain climate policies remain poorly understood.

This paper provides the first comprehensive assessment of the 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 arising from the inherent complexity of climate policy itself. Measuring climate policy uncertainty is challenging, however. We construct a novel measure of climate policy uncertainty based on newspaper coverage of topics related to uncertainty about the path of climate policy, and validate it through a comprehensive series of checks. 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 is complicated by a key identification challenge: changes in climate policy uncertainty are not always exogenous to the economy, as policymakers may adjust their climate stance in response to economic news. To confront this challenge, we identify 72 events that led to substantial increases in climate policy uncertainty but were mainly driven by climate-related, political or ideological considerations based on a comprehensive narrative account of the U.S. climate policy history. Examples include the shifting U.S. stance on international agreements like the Paris Accord, contentious debates over proposed but ultimately unsuccessful legislation such as cap-and-trade initiatives, or the EPA's inconsistent decisions to allow States to implement stricter emission standards. We quantify the importance of

an event by the extent of newspaper coverage surrounding it.

Using the climate policy uncertainty event 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 is approximately the shift in climate policy uncertainty from the last years of the Obama administration to the first Trump presidency, 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 1 percent and headline consumer prices rise by 0.4 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, interest rates do 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 to stabilize the economy and prevents even larger adverse impacts of policy uncertainty. Indeed, we show based on counterfactual analyses that monetary policy plays an important role for the transmission of climate policy uncertainty shocks. If the central bank were to accommodate the shock, in line with its response to other sources of economic policy uncertainty, the output response is largely stabilized. This comes 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 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. Thus, while uncertainty about future environmental regulations leads to emission reductions, this comes at a considerable economic cost.

While the shock leads to a substantial fall in private investment, government spending and investment remains unchanged, consistent with our interpretation of a shock mainly transmitting thrugh uncertainty as opposed to policy news. Furthermore, controlling for a newspaper-based index of climate policy news leaves our results virtually unchanged. Climate policy uncertainty shocks also have no significant impact on other measures of

uncertainty, including broader economic and trade policy uncertainty, geopolitical risk or financial uncertainty. This finding confirms the notion that climate policy uncertainty captures a distinct dimension of policy uncertainty.

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. Our analyses, based on the universe of U.S. listed firms, reveal that, on average, firms experience marked declines in key variables such as sales, employment, investment, and R&D expenses following a climate policy uncertainty shock. Specifically, firm-level sales and employment decline by around 0.9 percent, while investment and R&D expenses drop by 2.3 and 1.2 percent, respectively.

To further strengthen the interpretation of the shock, we show that firms respond more strongly to climate policy uncertainty when their exposure to climate change is high. For example, a one-standard-deviation increase in a firm's relative exposure leads to an additional 1.1 percent decline in investment and a 0.5 percent reduction in R&D expenses. Exploiting within-firm time-series variation allows us to flexibly control for confounding common aggregate and sector-specific factors.

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. Thus, we do find evidence for the green paradox at a disaggregated level: climate policy uncertainty incentivizes fossil-related sectors to accelerate brown projects due to the potential for stricter regulations in the future. However, R&D expenditure falls particularly strongly for these firms—suggesting that while climate policy uncertainty drives higher investment in fossil fuel-related sectors, likely by accelerating brown projects before stricter regulations are enacted, R&D activity to spur the green transition falls.

These results highlight how climate policy uncertainty can exacerbate transition costs through misallocative forces. Consistent with this notion, we document a persistent fall in total factor productivity—in the aggregate and at the firm level. These results further support the notion that climate policy uncertainty primarily transmit through supply-side channels.

A comprehensive series of sensitivity checks indicate that our results are robust along a number of dimensions, including the construction of the climate policy uncertainty indicator, our 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*. There is growing evidence that national climate policies are effective at reducing emissions (see e.g. Anderson, Marinescu, and Shor, 2019; Martin, De Preux, and Wagner, 2014). A number of studies have also analyzed the macroeconomic impacts of carbon prices. For European and Canadian carbon taxes, there is little evidence that they have significant economic effects (Metcalf, 2019; Metcalf and Stock, 2023; Bernard and Kichian, 2021). Känzig (2023) finds more significant effects for the European carbon market but shows that the economic costs depend crucially on how carbon revenues are distributed. Despite potential short-term economic costs, recent estimates of a very high social cost of carbon (Bilal and Känzig, 2024; Kotz, Levermann, and Wenz, 2024; Burke et al., 2023) underscore the urgency of implementing effective and predictable climate policy interventions.

However, in many countries including U.S., there have been few successful national climate policy initiatives. Yet, there has been substantial uncertainty about the future path of climate policy, leading to a growing interest in the economic impacts of climate policy *uncertainty*. Gavriilidis (2021), whose analysis this paper supersedes, was—to the best of our knowledge—the first to construct a news-based measure of climate policy uncertainty. Basaglia et al. (2021) use a similar approach but focus on the impact on firms' and investors' behavior. Noailly, Nowzohour, and Van Den Heuvel (2022) construct a measure of environmental policy uncertainty using a supervised machine learning approach but focus on the impact on green investment at the firm level. By contrast, we focus on the macroeconomic impacts of climate policy uncertainty and propose a novel instrument for identification.

Overall, our results illustrate that a clear and predictable path for climate policy is crucial to minimize economic costs during the transition to a greener, more sustainable economy. Fried, Novan, and Peterman (2021) study the impacts of climate policy uncertainty from a theoretical perspective. They show that uncertainty about future climate policy leads to a decrease in carbon emissions by causing investment to become relatively cleaner and output to fall, in line with our empirical findings. Furthermore, they show that a predictable carbon tax could achieve the same reduction in emissions at much lower cost.

Finally, our paper is related to an influential literature studying the role of uncertainty

for economic and financial fluctuations (see Bloom, 2014, for a survey). A key insight from this literature is that measuring uncertainty is not trivial. Methodologically, we build on a number of studies that take a news-based approach in spirit of Saiz and Simonsohn (2013) and proxy uncertainty by the coverage frequency of uncertainty-related topics in newspapers. This approach was first employed in the context of economic policy uncertainty (Baker, Bloom, and Davis, 2016) and later applied to geopolitical risk (Caldara and Iacoviello, 2022) and trade policy uncertainty (Caldara et al., 2020). Engle et al. (2020) rely on a similar approach to create an index of climate news that can be used to build climate change hedge portfolios. Sautner et al. (2023) measure climate change exposure at the firm level by analyzing earnings conference calls. We contribute to this literature by constructing a new measure of climate policy uncertainty and studying its impact on the macroeconomy. The result that climate policy uncertainty transmits differently to other policy uncertainty chimes well with Gambetti et al. (2023) emphasizing that the effects of uncertainty can crucially vary with other factors such as consumer disagreement.

Outline. The remainder of this paper is organized as follows. Section 2 discusses our approach to measure 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 arising from the inherent complexity of climate policy itself. 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 relatively broad, we constrain our definition along two dimensions. First, we take a macro approach considering climate policy with *national* significance. This means that we largely abstract from more 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 at local levels, the solutions are predominantly global in nature and are most likely to be shaped by national or supranational policies. Local-level uncertainty, while important, tends to be less central to the broader policy landscape addressing climate change. However, we do include some uncertainties about landmark state policy that influence the national discourse.

Second, we specifically focus on policy uncertainty related to *climate change*, abstracting from uncertainty surrounding environmental regulations unrelated to climate change—such as pollution control measures—or non-climate-related energy market regulations, such as those aimed at confronting energy shortages. This distinction is made because environmental regulations are often more narrow and local in nature, addressing specific issues that may be less salient in the context of global climate negotiations. Additionally, policies regarding energy shortages tend to be more endogenous to economic cycles, responding to fluctuations in energy prices or geopolitical factors rather than long-term climate objectives.

2.2. Measurement based on newspaper coverage

We measure climate policy uncertainty based on newspaper coverage of topics related to 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 topics related to uncertainties about climate policy are covered in the press.

Our sample consists of the text from 5.46 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, the *Wall Street Journal*, and the *Washington Post*. The selection of newspaper outlets is driven by their ability to provide comprehensive and systematic coverage of national climate policy developments. Given the specialized nature of climate policy, such coverage may be less detailed 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 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 method (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 coverage of topics related to climate policy uncertainty. This is a simple and transparent way to proxy the extent of climate policy uncertainty.

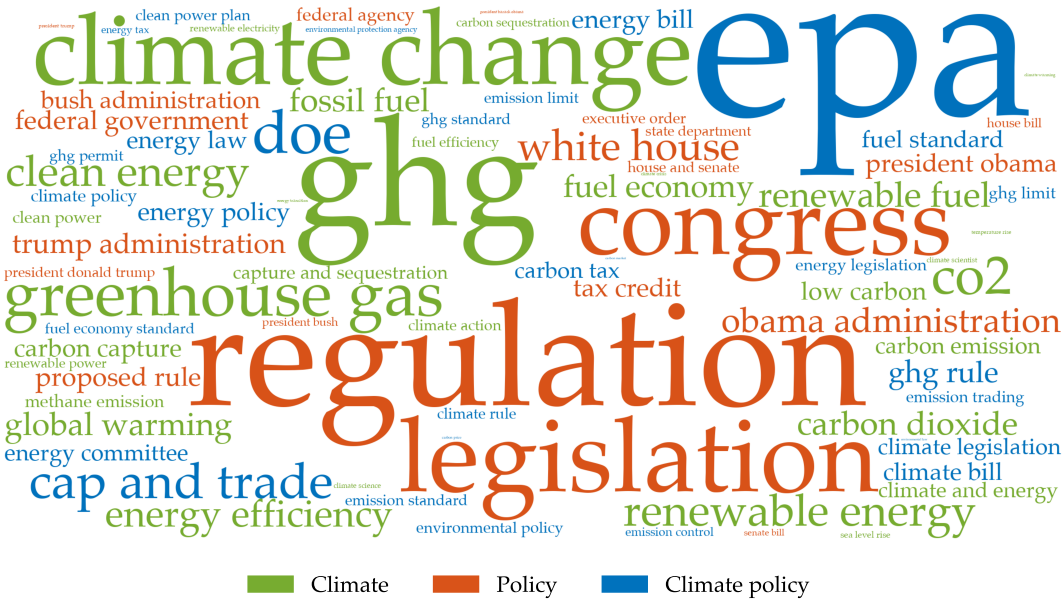
We construct three distinct dictionaries: one related to *climate change*, one on *policy*, and one concerning *uncertainty*. We also include a dictionary on *climate policy* containing terms that belong to both the climate change and policy dictionaries. An article is classified as discussing climate policy uncertainty if it contains at least one term from each of the climate change, policy, and uncertainty dictionaries, or if it contains a term from both the climate policy and uncertainty dictionaries.

How do we specify the information that guides the construction of the dictionaries? We draw on a corpus of news articles from agencies specializing in climate policy reporting, including *Inside Climate News*, *Inside EPA*, and *Washington Week (Energy)*. This climate policy news corpus dates back to the early 2000s and comprises around 26,500 news articles.

To construct the dictionaries, we follow a method similar to Aruoba and Drechsel (2024). First, we pre-process the data by splitting contractions and tokenizing the text. We then retrieve unigrams, bigrams and trigrams (n-grams), 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 corpus contains roughly 57,900 unigrams, 959,300 bigrams, and 1,636,200 trigrams. We calculate the frequency at which each n-gram occurs in our corpus. In a next

Figure 1: Climate policy dictionary



Notes: Word cloud illustrating the most common concepts in our climate, policy, and climate policy dictionaries

step, we rank each set of n-grams by their total frequency of occurrence across time. We then start with the most frequent trigram and move down, selecting concepts relevant to climate change, policy, or climate policy.[1] We repeat this procedure for bigrams and unigrams. When selecting the concepts, we are careful to select concepts that are sufficiently specific and not vague 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 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 dictionaries are illustrated in Figure 1, where the size of the concepts reflects its frequency in our climate policy news corpus.

For the uncertainty terms, 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.

Based on the articles identified as discussing climate policy uncertainty, we construct a climate policy uncertainty index, CPU_t. To construct the index, we count for each news-

[1]Multiple authors went through this selection independently and discussed disagreements. When moving down the frequency ranking, we stop at a generous lower bound.

paper the number of climate policy uncertainty articles in each month, scaled by the total number of articles in that period, $s_{i,t} = n_{i,t}^{\text{cpu}} / n_{i,t}^{\text{tot}}$ for $i \in \{\text{NYT}, \text{WSJ}, \text{WaPo}\}$. We standardize each monthly newspaper-level series to unit standard deviation and then construct an average across all the newspapers by month: $\text{CPU}_t = \frac{1}{3} \sum_i s_{i,t} / \sigma_i^s$. Finally, we normalize the averaged series to have a mean value of 100 for the whole period.

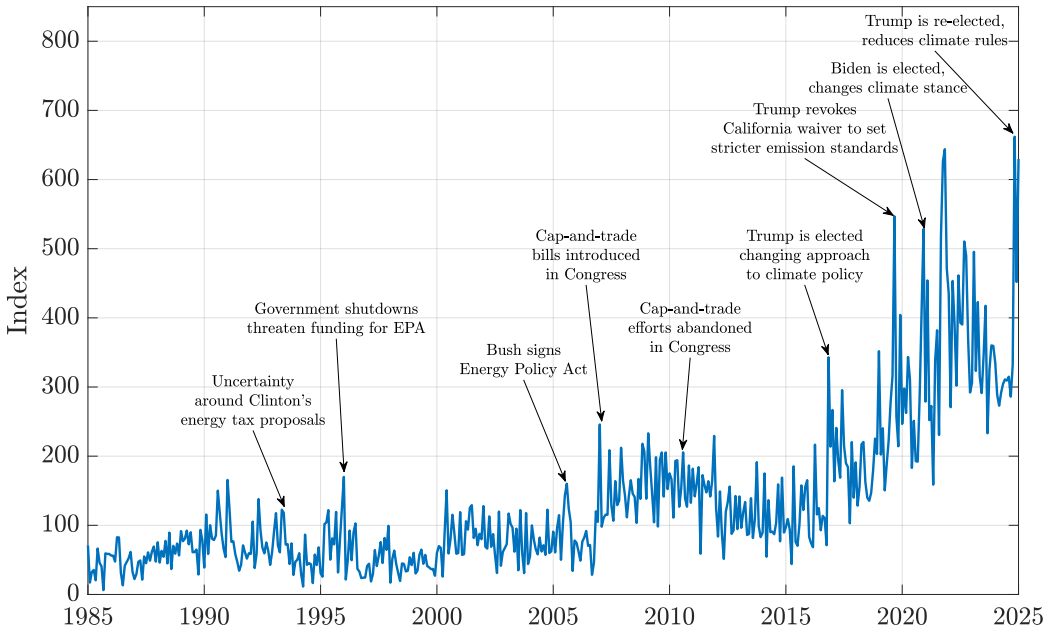
2.3. The climate policy uncertainty index

Figure 2 shows the constructed climate policy uncertainty index, from 1985 until recent years. At the beginning of our sample, uncertainty about climate policy was at a relatively low level. However, climate policy uncertainty started to increase in the late 1980s, when the U.S. ratified the Montreal protocol and remained elevated until the early to mid-1990s, when the U.S. amended the Clean Air Act and passed the first Energy Policy Act. There are also some notable spikes, for instance in early 1993 when there was growing opposition against Clinton's proposed energy tax, which ultimately led the President to back away from the proposal. At the end of 1995, a series of government shutdowns over budget disputes threatened the funding of the Environmental Protection Agency, causing uncertainty about climate regulations. Afterwards, climate policy uncertainty remained subdued until the early 2000s, when President Bush abandoned the Kyoto protocol and proposed a set of alternative climate and energy policies.

Around 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 Waxman-Markey Bill. 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 somewhat lower levels until the end of 2015, when the Paris agreement was adopted at the COP21 meeting. In April 2016, there is a notable spike in uncertainty when the agreement was open for signature, and the U.S. and China, among 175 parties, signed the agreement.

In November 2016, when Trump won the elections, climate policy uncertainty peaks. In the first months of the Trump presidency, climate policy uncertainty remained at historically high levels as the President dramatically changed the U.S. approach to climate change and announced to withdraw from the Paris agreement. In 2019, climate policy uncertainty spiked once more. Early in the year, momentum was building for initiatives to reduce greenhouse gas emissions, highlighted by the February introduction of the Green New Deal resolution by Alexandria Ocasio-Cortez and Ed Markey. However, these efforts faced significant setbacks later that year when the Trump administration revoked Califor-

Figure 2: The climate policy uncertainty index



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

nia's long-standing authority to set stricter vehicle emissions standards, effectively limiting states' ability to exceed national regulations. This marked the beginning of a new era of historically high levels of climate policy uncertainty. Following his election in November 2020, President Biden rejoined the Paris Agreement as one of his first acts in office, reaffirming the U.S.'s commitment to global climate action.

In 2021, climate policy uncertainty reached record levels as President Biden announced to restore the National Environmental Policy Act requirements, reversing Trump-era rollbacks, and later signed the Infrastructure Investment and Jobs Act and the Inflation Reduction Act, both of which included significant climate and clean energy investments. These actions marked a major shift in U.S. climate policy but also fueled uncertainty as industries adapted to new regulations amid a polarized political environment. With Trump's re-election, U.S. climate policy uncertainty reached a new all-time high and is poised to remain elevated for the foreseeable future.

2.4. Validation

To validate the index, we perform a number of validation exercises. First, we confirm that periods of historically high climate policy uncertainty indeed show up as spikes in our

climate policy uncertainty index. Second, we perform two audits—a human audit and an audit through a large language model—based on a subset of identified articles covering climate policy uncertainty (see Appendix A.3 for more information). A particular concern are false-positives. Our audits revealed that, due to the fairly specific dictionary terms used, only a negligible number of articles are false-positives. Finally, we analyze the sensitivity of our results with respect to the classification of climate policy uncertainty articles. We consider an alternative CPU index, based on a broader dictionary, as well as the original CPU index by Gavriilidis (2021) which is even less restrictive in terms of dictionary concepts. The results turn out to be remarkably robust.

We also show that our climate policy uncertainty index is only weakly correlated to other uncertainty measures from the literature. The correlation with the VXO is -0.01 and the correlation with the geopolitical risk index is 0.02. Unsurprisingly, climate policy uncertainty correlates somewhat more strongly with economic policy uncertainty as measured with the Baker, Bloom, and Davis (2016) index, with a correlation coefficient slightly below 0.5. This is to be expected given the focus on policy uncertainty with climate policy being one of the underlying dimensions. The correlation with the trade policy uncertainty index from Caldara et al. (2020) is 0.37. These moderate correlation coefficients illustrate that we are capturing distinct variation from other dimensions of policy uncertainty. Indeed, we will show in Section 4.3 that controlling for economic policy uncertainty and other policy uncertainty leaves our results virtually unchanged.

3. Identifying climate policy uncertainty shocks

How does uncertainty about climate policy affect the economy? Our measurement provides a suitable proxy of the extent of climate policy uncertainty in a given period. However, identifying the causal impact of climate policy uncertainty on macroeconomic outcomes presents a key challenge: changes in climate policy uncertainty are not always exogenous to the economy. Policymakers often adjust their climate policy agenda in response to economic conditions. Therefore, it is crucial to disentangle changes in uncertainty arising from economic dynamics from those that are independent of such considerations. Furthermore, while our index is designed to measure climate policy uncertainty according to our definition as well as possible, the measurement will never be perfect.

3.1. A new instrument based on major climate policy events

To confront these challenges, we seek to isolate some exogenous variation that is plausibly driven by U.S. climate policy uncertainty. To that end, we perform a comprehensive narrative account of the U.S. climate policy history.

Our idea is to identify events that led to substantial increases in climate policy uncertainty but were mainly driven by climate-related, political or ideological considerations. We focus on the period before 2020 for two main reasons. First, we want to avoid potentially confounding effects of the Covid-19 pandemic. Second, the Inflation Reduction Act (IRA) of 2022 represented a significant departure from the existing approach to climate policy in the United States. Prior to the IRA, U.S. climate policy was marked by fragmentation, inconsistency, and limited comprehensive federal action. Climate-related initiatives were predominantly short-term and vulnerable to legal challenges, creating an environment of significant policy uncertainty. Executive orders and temporary tax credits offered sporadic incentives, but failed to provide the sustained, systemic policy framework necessary for meaningful and predictable climate action. The Inflation Reduction Act with $369 billion in climate and energy investments disrupted this pattern, establishing long-term incentives and creating more stable policy signals.

Going through websites of government administrations, Congress, regulatory agencies, and newspapers, we identified 72 events leading to climate policy uncertainty over the period from 1985 to 2019. The events we identify as contributing to climate policy uncertainty span legislative, regulatory, presidential, and judicial actions. Table 1 provides a brief classification of the events we identify.

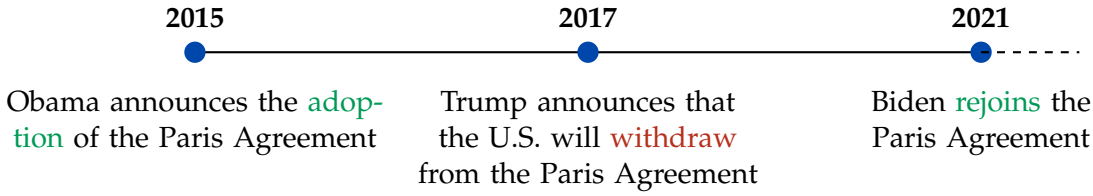
Table 1: Classification of climate policy uncertainty events

Event Type	**Count**
Advocacy	2
International agreements, treaties, and conventions	13
Judicial action	10
Legislative action	19
Political event	3
Presidential action	12
Regulatory action	13
Total	**72**

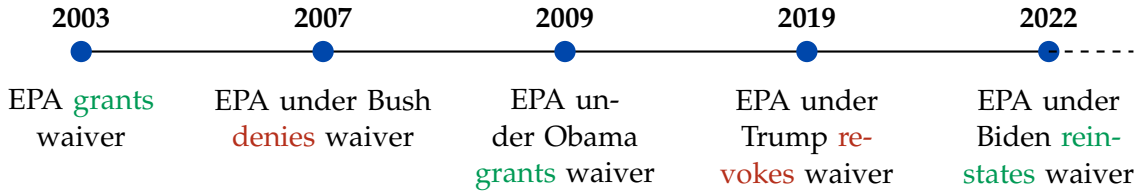
Notes: Overview of our identified climate policy uncertainty events and classification into different event types.

Figure 3: Illustrative U.S. climate policy timelines

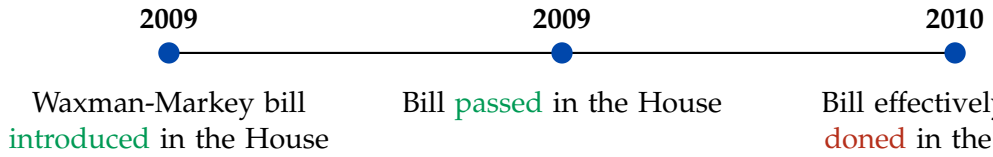
(a) Timeline of the U.S. stance on the Paris Climate Agreement



(b) Timeline of California's waiver to set stricter emissions standards



(c) Timeline of the Waxman-Markey bill

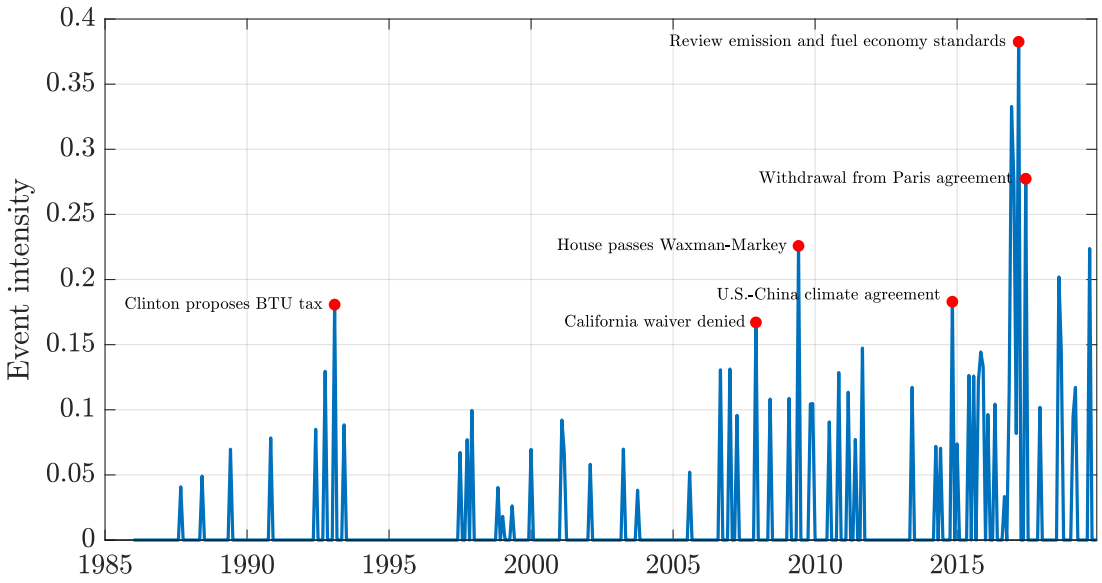


To illustrate the uncertainty in the events we identify, we discuss examples—including key international agreements, regulatory decisions, and legislative debates—where policies fluctuated significantly or were eventually abandoned. Figure 3a shows the timeline of the U.S. stance on the Paris Climate Agreement. In 2015, President Obama announced the adoption of the Paris Climate Agreement, committing reduce global greenhouse gas emissions. In 2017, President Trump announced that the U.S. will withdraw from the agreement, citing concerns about economic impacts. In 2021, on his first day in office, President Biden rejoined the agreement, committing to address climate change. Such fluctuations give rise to uncertainty in the path of the climate policy. Similarly, as shown in Figure 3b, fluctuations in regulatory actions occurred over California's request for a waiver to set stricter emission standards than those implemented at the national level. Finally, legislative actions, such as the Waxman-Markey bill shown in Figure 3c, failed to gain sufficient support in the Senate after passing the House, leading to uncertainty about the future of a national cap-and-trade system.

To quantify the importance of each event, we leverage again the information contained in leading U.S. newspapers. Specifically, for each event, we count the number of articles

that are classified as related to climate policy on the event day and the two days following the event.[2] We normalize this count by the total number of articles published during the event window. The approach is similar in spirit to Baker, Bloom, and Terry (2024). In a final step, we aggregate the daily event series to a monthly series by summing over the normalized counts in a given month. In months with no events, the series takes zero value. For more information on the construction of our instrument, see Appendix B.

Figure 4: Major climate policy uncertainty events



Notes: Climate policy uncertainty events, where the magnitude indicates the extent of event coverage in newspapers on the event day and the following two days.

Figure 4 shows the climate policy uncertainty event series, capturing the intensity of events driving climate policy uncertainty. 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 three key periods, the early 1990s, the late 2000s and from mid-2010 onwards, the series is serially correlated. However, our results are robust to using a residualized version of the instrument purged from autocorrelation as suggested by Miranda-Agrippino and Ricco (2021), see Figure D.8 in the appendix. 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

[2]We varied the event window and the results turn out to be robust to the exact event window used.

of 0.70. Finally, we show that the instrument is uncorrelated with other structural shock measures from the literature, including uncertainty, oil, productivity, news, monetary policy, financial, and fiscal policy 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.

As an alternative to our instrumental variables approach, we will rely on timing assumptions commonly used in the policy uncertainty literature (e.g. in Baker, Bloom, and Davis, 2016). The idea is to leverage the fact that the political process is rigid and may respond to macroeconomic developments only with a lag. Specifically, we assume that climate policy uncertainty is not affected by macroeconomic fluctuations in the current month. This amounts to controlling for lagged macroeconomic variables in our empirical specification.

3.2. Econometric framework

To estimate the dynamic causal effects of climate policy uncertainty, we rely on VAR techniques. In this way, we estimate an aggregate effect of climate policy uncertainty, including any general equilibrium adjustments. Starting point is the following VAR model:

$$\mathbf{y}_t = \mathbf{b} + \mathbf{B}_1 \mathbf{y}_{t-1} + \cdots + \mathbf{B}_p \mathbf{y}_{t-p} + \mathbf{u}_t, \tag{1}$$

where p is the lag order, $\mathbf{y}_t$ is a $n \times 1$ vector of endogenous variables, $\mathbf{u}_t$ is a $n \times 1$ vector of reduced-form innovations with covariance matrix $\text{Var}(\mathbf{u}_t) = \mathbf{\Sigma}$, $\mathbf{b}$ is a $n \times 1$ vector of constants, and $\mathbf{B}_1, \ldots, \mathbf{B}_p$ are $n \times n$ coefficient matrices.

Assuming that the VAR is invertible, we can write the innovations $\mathbf{u}_t$ as linear combinations of the structural shocks $\boldsymbol{\varepsilon}_t$:

$$\mathbf{u}_t = \mathbf{S}\boldsymbol{\varepsilon}_t. \tag{2}$$

By definition, the structural shocks are mutually uncorrelated, i.e. $\text{Var}(\boldsymbol{\varepsilon}_t) = \mathbf{\Omega}$ is diagonal. From the invertibility assumption (2), we get the standard covariance restrictions $\mathbf{\Sigma} = \mathbf{S}\mathbf{\Omega}\mathbf{S}'$.

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 our series of major climate policy uncertainty events.

External instrument approach. Given the instrument z_t, in our case the climate policy uncertainty event series, identification can be achieved as follows. 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:

$$\mathbb{E}[z_t \varepsilon_{1,t}] = \alpha \neq 0 \tag{3}$$

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{2:n,t}] = \mathbf{0}, \tag{4}$$

where assumption (3) is the relevance requirement and assumption (4) is the exogeneity condition. These assumptions, in combination with the invertibility requirement (2), identify $\mathbf{s}_1$ up to sign and scale:

$$\mathbf{s}_1 \propto \frac{\mathbb{E}[z_t \mathbf{u}_t]}{\mathbb{E}[z_t u_{1,t}]}, \tag{5}$$

provided that $E[z_t u_{1,t}] \neq 0$.[3] We implement the estimator with a 2SLS procedure and estimate the coefficients above by regressing $\hat{\mathbf{u}}_t$ on $\hat{u}_{1,t}$ 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 vecor is given by $s_1 = [\text{chol}(\boldsymbol{\Sigma})]_{\cdot,1}$.

Local projections. The VAR approach tends to be efficient, allowing for sharper inference. However it relies on two potentially restrictive assumptions. The first is invertibility, meaning that the model incorporates all relevant information needed to recover the structural shocks of interest. The second pertains to the dynamic VAR structure, with the key assumption being that a finite-order VAR adequately approximates the dynamics of the data generating process.

To assess how restrictive these assumptions are, we estimate the responses to a climate policy uncertainty shock using local projections à la Jordà (2005). Specifically, we use a lo-

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

cal projections-instrumental variable approach (Jordà, Schularick, and Taylor, 2015). This amounts to directly estimating the dynamic causal effects of a climate policy uncertainty shock from the following set of regressions:

$$y_{i,t+h} = \alpha_h^i + \theta_h^i y_{1,t} + \boldsymbol{\beta}_h^{i\prime} \mathbf{x}_{t-1} + \nu_{i,t,h}, \tag{6}$$

using z_t as an instrument for $y_{1,t}$. Here, $y_{i,t+h}$ is the outcome variable of interest, $y_{1,t}$ is the endogenous regressor, $\mathbf{x}_{t-1}$ is a vector of controls, $\nu_{i,t,h}$ is a potentially serially correlated error term, and h is the impulse response horizon. We use the same controls as in the VAR. For inference, we follow again the lag-augmentation approach proposed by Montiel Olea and Plagborg-Møller (2020).

For identification, we have to assume in addition to (3)-(4) that the instrument is orthogonal to leads and lags of the structural shocks:

$$\mathbb{E}[z_t \boldsymbol{\varepsilon}_{t+j}] = \mathbf{0}, \quad \text{for } j \neq 0. \tag{7}$$

In return, we can dispense of the invertibility assumption underlying equation (2). Furthermore, because we estimate the dynamic causal effects directly without extrapolating from the first autocovariances, the approach is also less subject to lag truncation bias.

To assess the extent of lag truncation bias, we alternatively estimate the impulse responses to the climate policy uncertainty VAR shock using local projections. To fix ideas, we first extract the climate policy uncertainty shock from the monthly VAR as $\varepsilon_{1,t} = \mathbf{s}_1' \boldsymbol{\Sigma}^{-1} \mathbf{u}_t$ (for a derivation, see Stock and Watson, 2018). Next, we estimate the effects for the additional variables of interest y_i using simple local projections:

$$y_{i,t+h} = \alpha_{h,0}^i + \theta_h^i \varepsilon_{1,t} + \beta_{h,1}^i y_{i,t-1} + \ldots + \beta_{h,p}^i y_{i,t-p} + \nu_{i,t,h}, \tag{8}$$

where θ_h^i is the effect on variable i at horizon h. This approach assumes (partial) invertibility, but relaxes the dynamic VAR structure, directly estimating the impulse responses to the shock of interest.

An additional appeal of this approach is that it allows to estimate the effects on variables that are only available at a lower frequency, such as on a quarterly or even annual basis. In this case, we aggregate the shock $\varepsilon_{1,t}$ by summing over the respective months before running the local projections. This mitigates the problem that external instruments, when aggregated to the quarterly or annual frequency, often lack the power to credibly estimate the effects of interest (c.f. Nakamura and Steinsson, 2018).

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 producer price index for all commodities. 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 and we end the sample in 2019, before the outbreak of the Covid-19 pandemic. We include the unemployment rate and the 3-month 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.

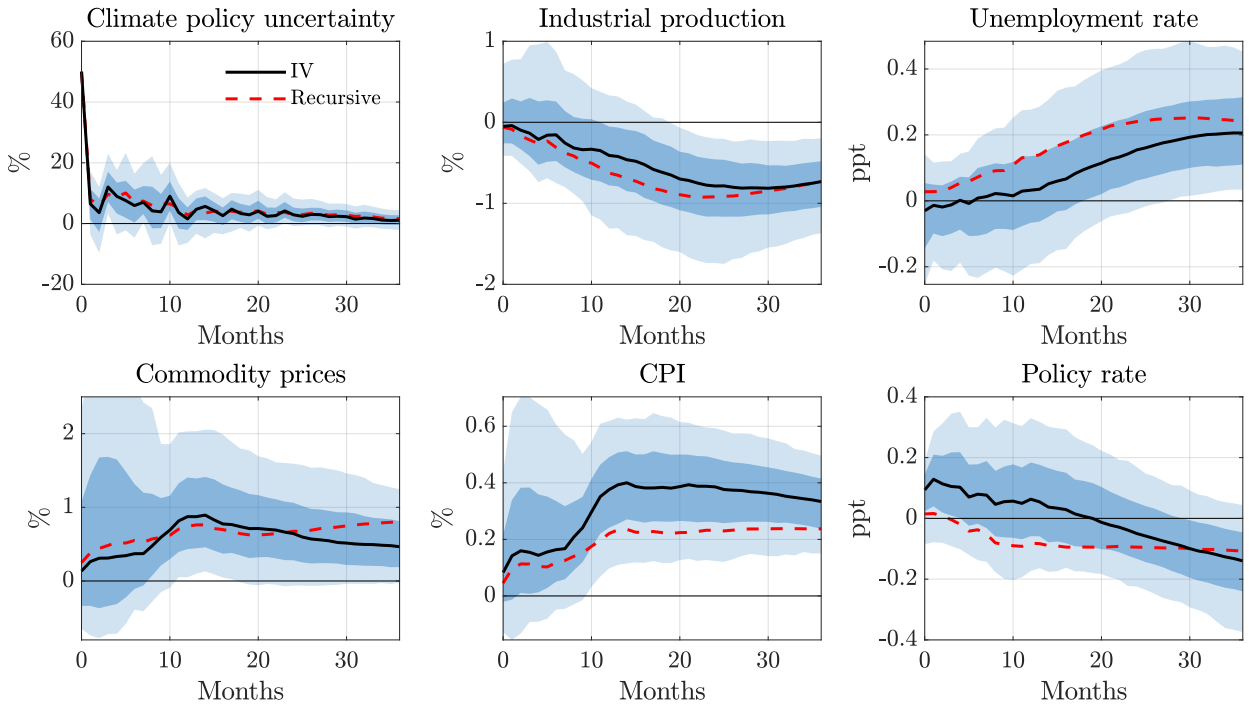
4. The effect on the macroeconomy

How does climate policy uncertainty affect the macroeconomy? In this section, we present the results based on our VAR model for the United States. Because our uncertainty indices have an arbitrary scale, we normalize the shock to increase climate policy uncertainty by 50 percent. This is approximately the increase we observed during the first Trump presidency years, compared to the final years of the Obama administration.

Figure 5 shows the impulse responses to a climate policy uncertainty shock, estimated based on the external instruments VAR approach. The robust first-stage F-statistic is 10.10 and thus just above the commonly used threshold of 10. We thus proceed by 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 an increase in the CPU index that persists for about a year. This has significant implications for the U.S. economy. Industrial production declines, reaching a trough of approximately -0.8 percent after two years, while the unemployment rate increases by 0.2 percentage points. Notably, the shock also leads to an increase in prices: commodity prices increase gradually, reaching about 1 percent after a year, and headline consumer prices rise by around 0.4 percent. These responses

Figure 5: Impulse responses to a climate policy uncertainty shock



First-stage regression: F-Statistic: 10.10, R^2: 1.68%

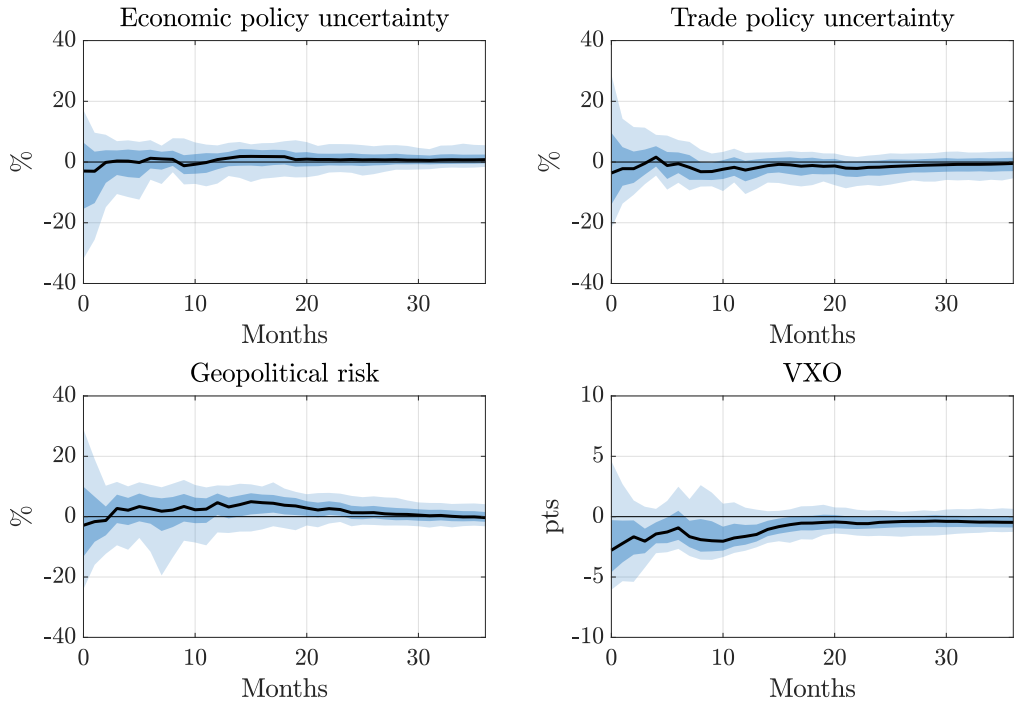
Notes: Impulse responses to a climate policy uncertainty shock, normalized to increase the CPU index by 50 percent on impact, estimated from the external instruments VAR using the climate policy uncertainty event series as an instrument. The black line is the point estimate and the dark and light blue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

are statistically significant at the 90 percent confidence level, at least for some horizons. The divergence between price and activity dynamics creates a trade-off for monetary policy. In the short term, monetary policy leans against the inflationary pressures, while in the longer term, it accommodates the fall in economic activity. However, it is important to note that the monetary policy response is imprecisely estimated and not statistically significant at the 90 percent level.

We also present the impulse responses from the model identified based on short-run timing restrictions as the red dashed line. We only show the point estimates in Figure 5, for the confidence bands, see Figure D.4 in Appendix D. Interestingly, the responses turn out to be broadly comparable to our baseline, external instruments VAR with some notable differences. The responses of the CPU, industrial production and commodity prices are very similar, while the CPI response is less pronounced, and the interest rate response suggests a more accommodative monetary policy response. This may reflect the fact that the recursive approach is not completely successful at identifying exogenous increases

in climate policy uncertainty. Another difference lies in the estimation uncertainty. The stronger identifying assumptions underlying the recursive approach drastically improve precision, as can be seen from the much narrower confidence bands in Figure D.4.

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 by 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.

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. From the top panel, we observe that the response of economic policy uncertainty and trade policy uncertainty remain close to zero and are statistically insignificant. Similarly, the bottom panel shows no evidence of an increase in geopolitical risk following the shock. Financial uncertainty, measured by the VXO, exhibits a slight tendency to decline, though this effect is not statistically significant.

Overall, these findings indicate that the shock represents a distinct source of policy uncertainty specific to climate-related issues, reinforcing the validity of our identification

strategy.

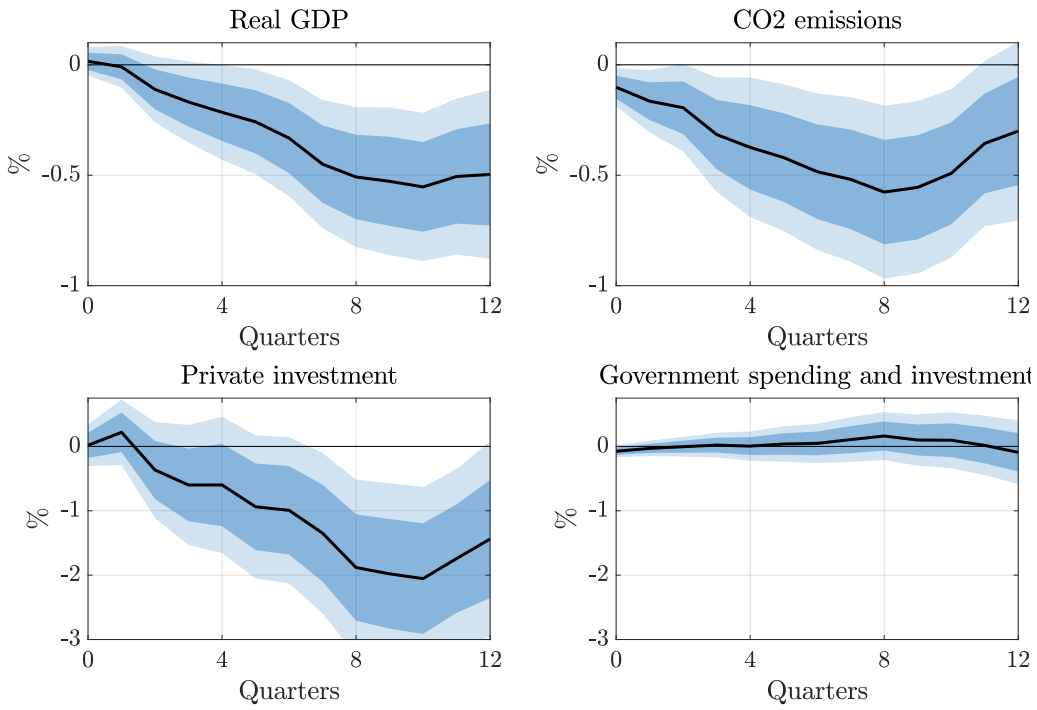
To get a better understanding of how climate policy uncertainty shocks transmit to the macroeconomy, we study the effects on a selection of macroeconomic variables, including GDP, emissions, and investment. These variables are only available at the quarterly frequency, where our external instruments 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.

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 and reaches a trough at about -0.4 percent. The shape of the response mirrors the response of industrial production. Climate policy uncertainty also leads to a significant fall in CO2 emissions. However, the reduction in emissions seems to be largely driven by the fall in activity and not by improvements in the emissions intensity in production, as the emissions response mirrors the response of industrial production quite closely. This result is consistent with the findings in Fried, Novan, and Peterman (2021). While the fall in emissions is certainly positive from an environmental perspective, it does come at a significant economic cost. Indeed, the existing empirical evidence suggests that climate policies such as carbon taxes or cap-and-trade systems can deliver emissions reductions at lower cost (see e.g. Känzig, 2023; Metcalf and Stock, 2023).

We thus do not find evidence for the green paradox, at least at the macro level (see e.g. Sinn, 2008). According to this literature, uncertainty about future climate policy would drive up current emissions by increasing incentives to extract fossil fuel, leading to an expansion in current supply. 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 over -1.5 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 finding strengthens our interpretation of the shock as stemming largely from uncertainty rather than news. If the identified shock mainly captured actual climate policy news, we would expect to see a change in government spending. The lack of response in govern-

Figure 7: Impacts on GDP, emissions and investment



Notes: Impulse responses of GDP, emissions and investment to a climate policy uncertainty shock, estimated by local projections (8) on the aggregated climate policy 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.

ment spending and investment thus supports the view that the shock primarily reflects elevated climate policy uncertainty, not policy news. In the sensitivity Section 4.3, we will also show that explicitly controlling for an index of climate policy news leaves our results virtually unchanged.

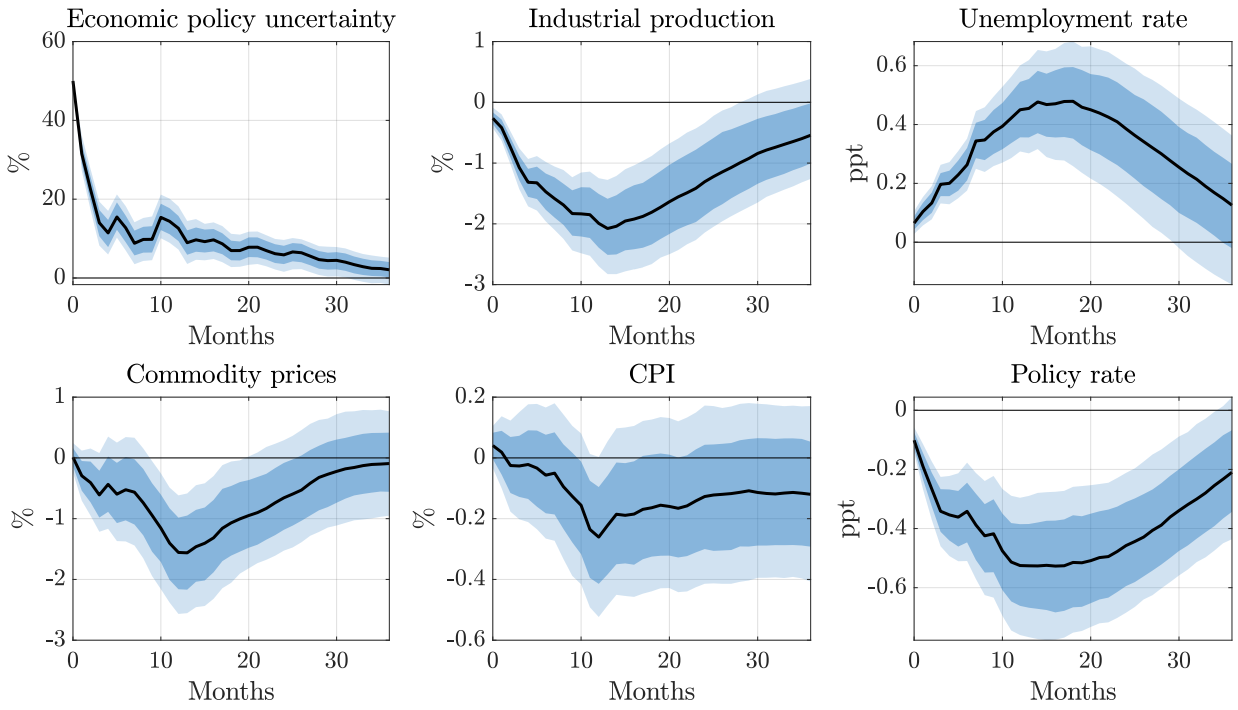
4.1. Climate vs. economic policy uncertainty

We have seen that climate policy uncertainty shocks have substantial macroeconomic consequences. This aligns with a well-established literature highlighting uncertainty and risk as key 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. 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. Specifi-

cally, we assume that economic policy uncertainty is affected by macroeconomic variables only with a lag. We normalize the shock again to increase economic policy uncertainty by 50 percent on impact.

Figure 8: Impulse responses to an economic policy uncertainty shock



Notes: Impulse responses to an economic policy uncertainty shock, normalized to increase the EPU index by 50 percent on impact, estimated based on 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.

Figure 8 presents the results. Following the 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 -2 percent, while the unemployment rate increases by around 0.4 percentage points. These effects on economic activity are at least qualitatively similar to the impacts of climate policy uncertainty, even though the responses are more pronounced but less persistent.

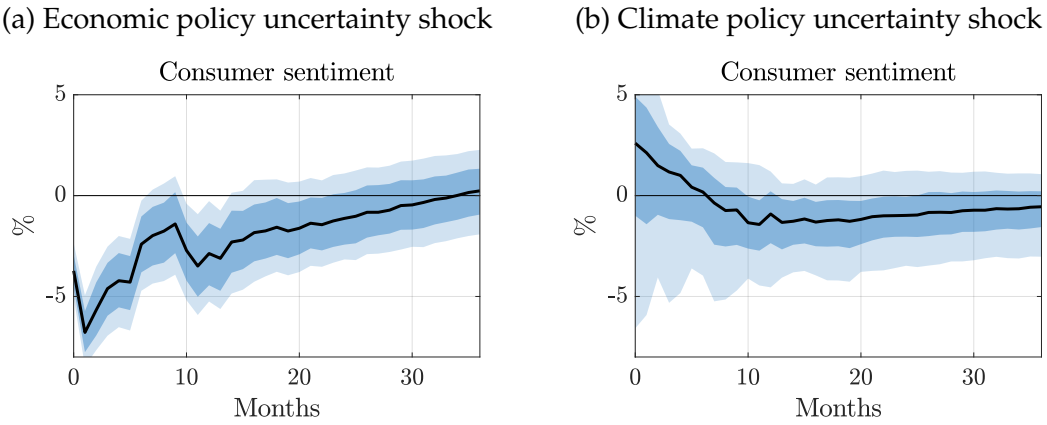
However, the price responses of the two shocks differ fundamentally. Whereas climate policy uncertainty leads to an *increase* in commodity and consumer prices, economic policy uncertainty leads to a *fall* in both prices. Thus, economic policy uncertainty shocks appear to transmit primarily as demand shocks, consistent with the findings 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 drasti-

cally 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 climate policy uncertainty shocks, at least in the short term.

Why does climate policy uncertainty shocks increase prices while broader economic policy uncertainty leads to a fall in prices? Our results suggest that climate policy uncertainty shocks mainly transmit through supply-side channels such as the real-options channel (see e.g. Dixit and Pindyck, 1994; Bloom, 2009), causing firms to delay investment and hiring after a rise in uncertainty, or the precautionary pricing channel (Born and Pfeifer, 2014; Fernández-Villaverde et al., 2015), working through the potential for higher future marginal costs, causing firms to raise prices preemptively. Economic policy uncertainty shocks instead seem transmit more trough the demand side, for instance through precautionary saving (Baker, Bloom, and Davis, 2016), leading to a fall in demand as agents cut their spending.

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: Impacts on consumer sentiment



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

The results are depicted in Figure 9. The left panel 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 pol-

icy uncertainty shocks, leading to weaker demand for goods and services. This reduced demand in turn may further discourage firms from investing, either due to anticipated lower returns or financial constraints.

In contrast, the right panel shows that climate policy uncertainty shocks have no significant effect on consumer sentiment. This suggests that climate policy uncertainty transmits primarily through supply-side channels. Overall, these results reinforce the notion that economic policy uncertainty propagate more like demand and climate policy uncertainty like supply shocks.

4.2. The role of monetary policy

We have seen that 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 response. This is very different from how monetary policy responds to other sources of uncertainty, which tend to propagate more like demand shocks and are accommodated by the central bank.

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. Specifically, we rely on 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. By only using a combination of shocks on impact, the contemplated counterfactual policy is incorporated in private-sector expectations ex-ante and thus robust to the Lucas critique.

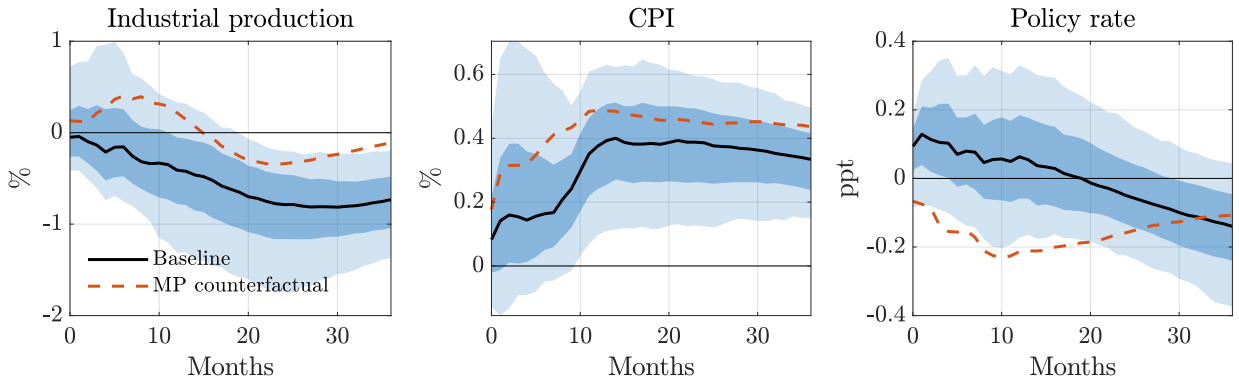
The counterfactual that we are interested in is to study the impacts of climate policy uncertainty in a scenario where monetary policy responds to these shocks in the same way as to economic policy uncertainty shocks more broadly.[4] To condition the response, we identify a monetary policy shock using the high-frequency surprises around FOMC announcements from Bauer and Swanson (2023), purged from relevant macroeconomic and financial data predating the announcement.[5]

The results from the counterfactual exercise are shown in Figure 10. By accommodating the climate policy uncertainty shock, monetary policy is able to largely stabilize

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

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

Figure 10: Monetary policy counterfactual



Notes: Impulse responses to a climate policy uncertainty shock based on our baseline model and under a counterfactual monetary policy response, imposing the same monetary response as to EPU shocks. The lines are the point estimates and the dark and light blue shaded areas are 68 and 90 percent confidence bands based on the external instruments VAR.

the industrial production response. This comes at a cost of somewhat 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 policy makers could exploit, even though the optimal monetary policy response will depend of course on the policymaker's loss function.

Overall, these results highlight the significant role that monetary policy plays in the transmission of climate policy uncertainty shocks. They underscore the need for a coordinated approach between fiscal and monetary policies to effectively address the climate challenge. Successful climate action requires that both policy areas work together to mitigate the economic impacts of uncertainty and support long-term sustainability goals.

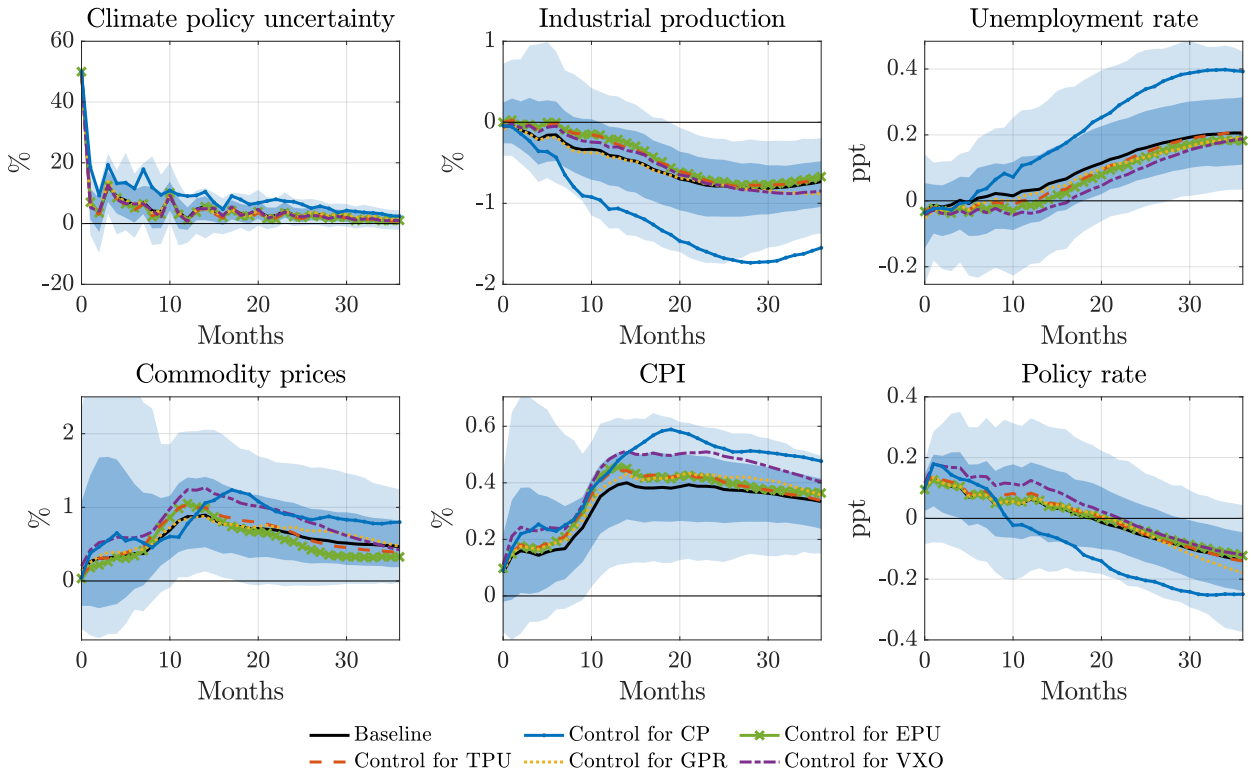
4.3. Sensitivity

In this section, we perform a comprehensive series of sensitivity checks on our identification strategy and empirical specification.

To further mitigate concerns that we are mainly picking up climate policy *news* as opposed to *uncertainty*, we construct a climate policy (CP) news index. This follows the construction of our CPU index, described in Section 2, but dropping the requirement for articles to also contain words from the uncertainty dictionary. The idea is to isolate some variation in our CPU index that is not driven by policy news.

The results are shown in Figure 11. Controlling for the climate policy news index does not change the responses materially. All responses are qualitatively similar, and if

Figure 11: Controlling for climate policy news and other uncertainty measures



Notes: Impulse responses to a climate policy uncertainty shock, normalized to increase the CPU index by 50 percent on impact. The figure compares our baseline response (black) to the responses from models where we control for climate policy news (blue), for economic policy uncertainty (green), for trade policy uncertainty (red), for geopolitical risk (yellow) and for the VXO (purple). The dark and light blue shaded areas are 68 and 90 percent confidence bands from our baseline external instruments VAR.

at all the effects are even more pronounced, especially at longer horizons. This is consistent with the estimated climate policy uncertainty response, which turns out to be more persistent when controlling for climate policy news.

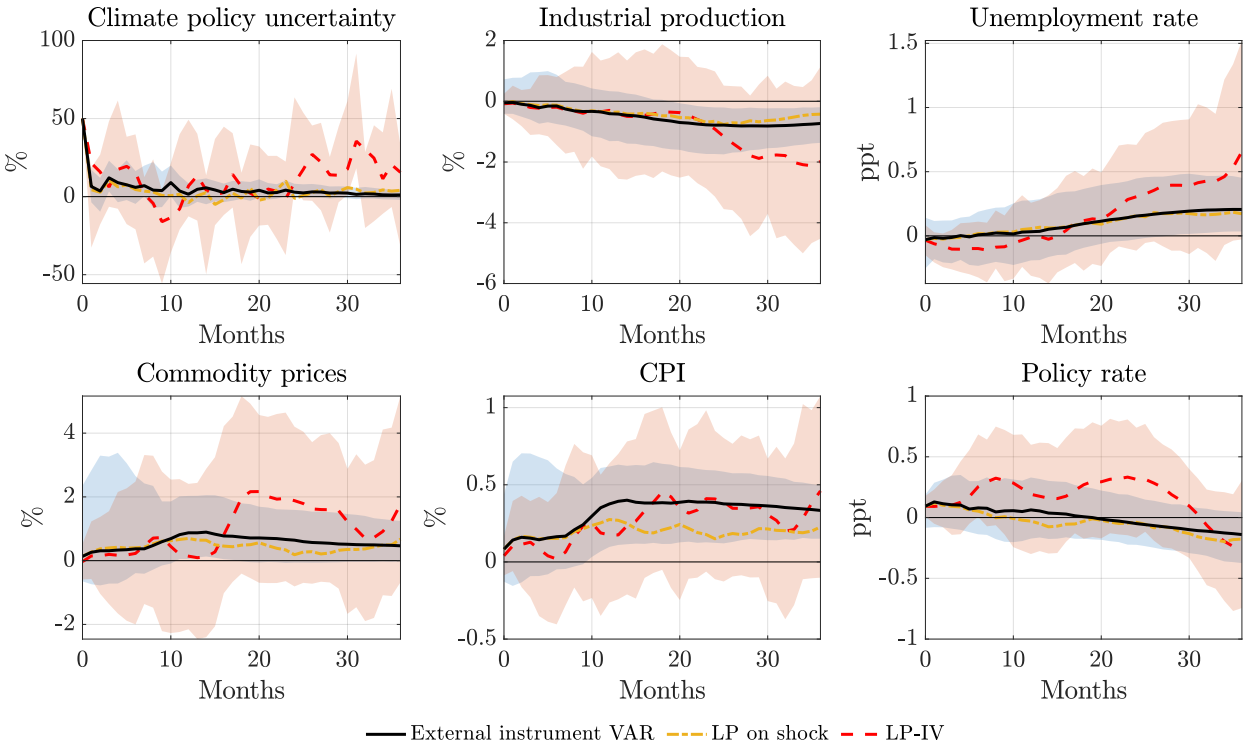
We have seen that climate policy uncertainty shocks have no meaningful impact on other uncertainty variables. An important questions is how our baseline responses change when controlling for other dimensions of uncertainty. From Figure 11, we can see that the results are virtually unchanged when controlling for economic policy uncertainty, trade policy uncertainty or geopolitical risk. When controlling for the VXO, the price responses turn out to be more pronounced but overall the responses are again very similar. These results reinforce the notion that we are capturing uncertainty specific to climate policy and not broader economic or financial uncertainty.

Our external instruments VAR approach relies on some potentially restrictive assump-

tions, in particular invertibility and a negligible 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. Figure 12 presents the results. Overall, the responses turn out to be very similar to our baseline responses. Only the CPI response turns out to be less persistent when estimated directly using local projections. These results suggest 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 in our VAR model.

Figure 12: Sensitivity with respect to VAR assumptions



Notes: Impulse responses to a climate policy uncertainty shock, estimated based on the external instruments VAR (black), the LP-IV specification (red dashed), the LP on the VAR shock measure (yellow dash-dot). The lines are the point estimates and the light blue and red shaded areas are 90 percent confidence bands for the external instruments VAR and the LP-IV, respectively.

Lastly, we present results based on an even less restrictive local projections-instrumental variable specification, which is robust to non-invertibility issues. As expected, the responses turn out to be much more noisy. However, qualitatively the re-

sponses are very similar to our baseline responses from the external instruments VAR. Thus, we do not find much evidence that the invertibility assumption is overly restrictive in our context. The main advantage of the VAR approach lies in its precision. As we can see in Figure 11, the LP-IV responses are much less precisely estimated, making it difficult to draw meaningful conclusions from the evidence.

We also assess the sensitivity with respect to the measurement of climate policy uncertainty. Figure D.1 in Appendix D.2 shows the impulse responses using our broader CPU index, measured based on slightly less restrictive dictionary criteria, and the original index in Gavriilidis (2021), which is in turn based on even less specific keywords. The results turn out to be robust to the measurement of climate policy uncertainty. This illustrates the advantage of our external instruments approach, leveraging information specific to major climate policy uncertainty events. Furthermore, using an index that leverages a larger set of newspapers, as in Baker, Bloom, and Davis (2016), also produces very similar results.

Finally, we study the sensitivity 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. See Appendix D.2 for more information.

5. Firm-level and sectoral impacts

We have established that climate policy uncertainty has significant macroeconomic consequences. In this section, we examine its effects at the firm level. This serves two purposes. First, examining firm-level impacts is valuable in its own right, as it allows us to uncover underlying heterogeneities in the average responses. Second, focusing on within-firm variation allows us to better control for confounding factors through fixed effects. We begin by analyzing how firm-level variables respond, on average, to a climate policy uncertainty shock.

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 not available 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

To estimate the dynamic causal effects of a climate policy uncertainty shock in the panel, we use the panel local projections method. This method allows us to estimate the average effect of a climate policy uncertainty shock across firms, controlling for time-variant firm characteristics. Specifically, we estimate the following series of panel regressions for each horizon h:

$$y_{j,t+h} = \alpha_{j,h} + \theta_h \varepsilon_{1,t} + \boldsymbol{\beta}_h' \mathbf{x}_{j,t-1} + \nu_{j,t+h} \tag{9}$$

where, $y_{j,t}$ is the (log) outcome variable of interest for firm j at time t[6], $\alpha_{j,h}$ 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, and in some cases, only at the annual frequency. As noted earlier, we thus aggregate the monthly climate policy uncertainty shock from the VAR accordingly before implementing the local projections, as detailed in Section 3.2.

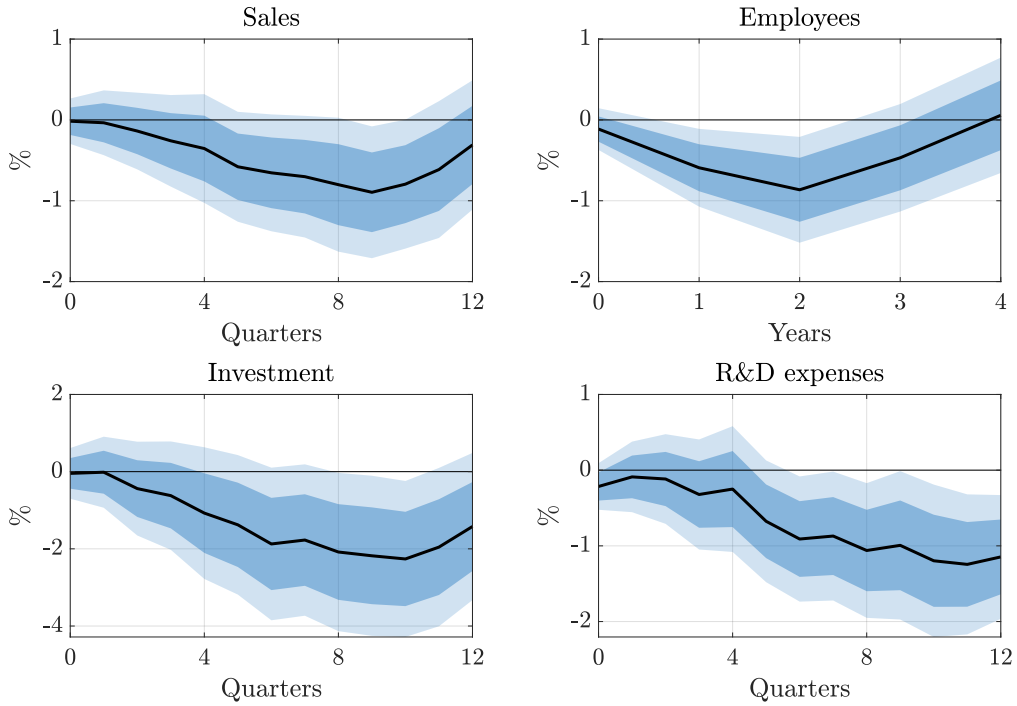
For the quarterly specification, we include four lags of the dependent variable, four lags of the shock, and a linear time trend as controls, consistent with our baseline specification for aggregate variables. We also include quarter fixed effects to account for seasonality in the outcome variable, though 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) with 11,872 firms, which, net of missing data, amounts to 644,272 observations. For inference, following Almuzara and Sancibrián (2024), we use heteroskedasticity-robust standard errors clustered at the time level with sufficient lags as controls.

Figure 13 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 0.9 percent after two years. This result is quantitatively similar to the response of aggregate industrial production in the VAR (see Figure 5) and qualitatively similar to that of aggregate real GDP in

[6]To economize on notation, we omit the variable index i in $y_{i,j,t}$.

Figure 13: Average effect of climate policy uncertainty shock



Notes: Average response of firm-level variables to a climate policy uncertainty shock, estimated by panel local projections (9) on the aggregated climate policy shock extracted from our baseline external instruments VAR. All variables are converted to real terms using the deflator series. Solid lines represent point estimates, while the dark and light shaded areas indicate 68 and 90 percent confidence bands, respectively. Standard errors are clustered by time, following Almuzara and Sancibrián (2024).

the local projections (see Figure 7). Average employment also falls by close to 0.9 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 2.3 percent after two years, consistent with the response of aggregate private investment. Finally, R&D expenses also decline significantly by 1.2 percent. The decline in average investment and R&D expenses at the firm-level, alongside the decline in employment, strengthens our finding that the climate policy uncertainty shock primarily transmits through supply-side channels.

5.2. Heterogeneous effects of climate policy uncertainty

Thus far, we have shown that the average effects of climate policy uncertainty at the firm level largely mirror its aggregate effects. However, firms may exhibit heterogeneous responses to climate policy uncertainty along important dimensions. 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 prior exposure to climate change. We are interested in 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 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 4,165 firms from 2001 to 2019 (76 quarters), yielding 136,039 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:

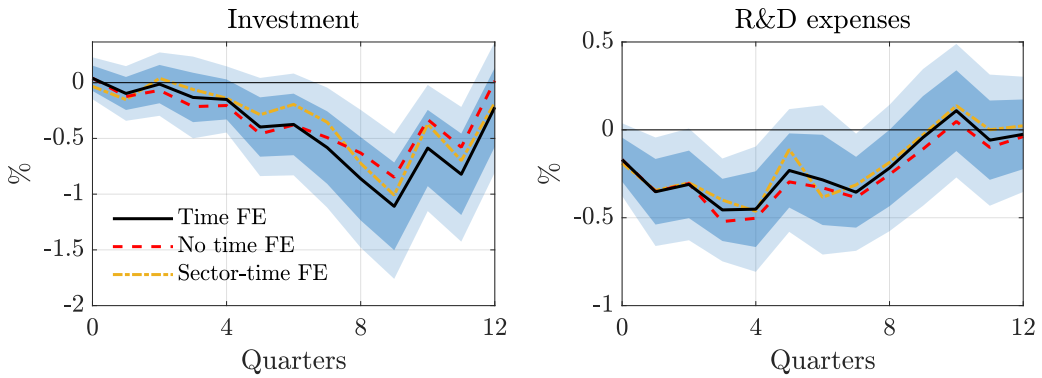
$$y_{j,t+h} = \alpha_{j,h} + \delta_t + \gamma_h(\text{Exp}_{j,t-1} - \overline{\text{Exp}_j}) \times \varepsilon_{1,t} + \boldsymbol{\beta}_h' \mathbf{x}_{j,t-1} + \nu_{j,t+h}, \tag{10}$$

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 θ_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 includes no time fixed effects but the same controls as in (9). Our most restrictive specification includes sector by time fixed effects, controlling for common sector specific trends.

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

Figure 14: 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 by the interaction of the climate policy uncertainty VAR shock and the firm-level prior climate policy exposure in the panel local projection (10). All variables are converted to real terms using the deflator series. Solid lines represent point estimates, while the dark and light shaded areas indicate 68 and 90 percent confidence bands, respectively. Standard errors are clustered by time, following Almuzara and Sancibrián (2024).

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.

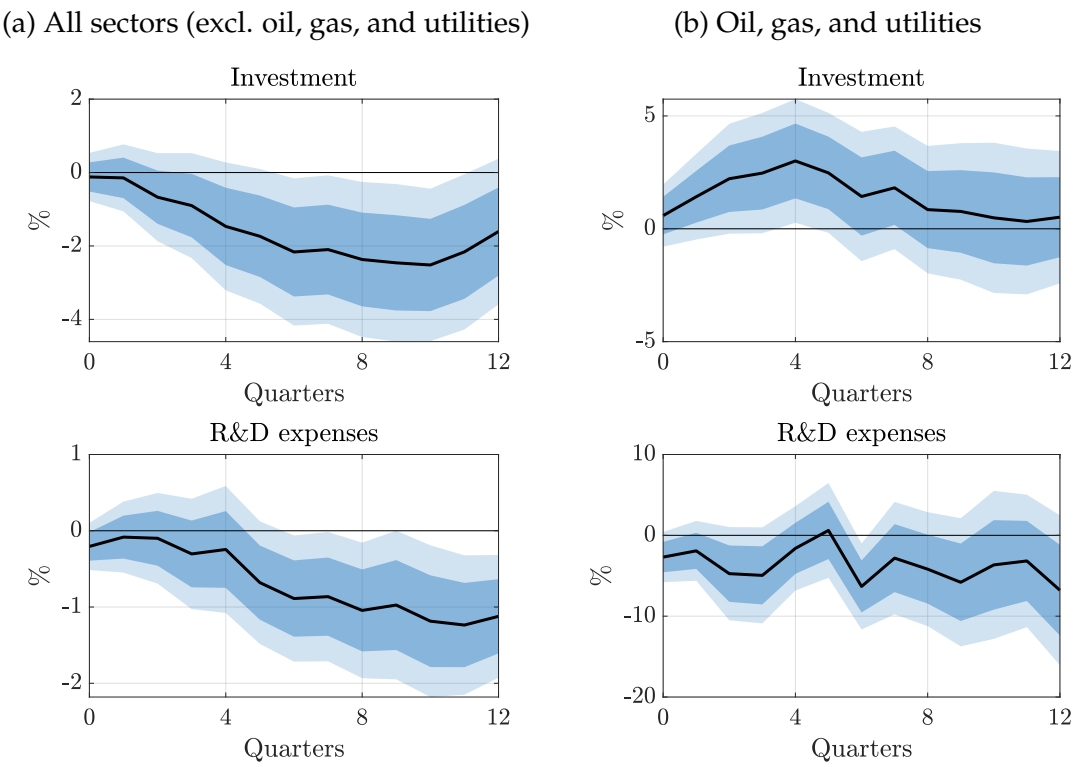
Consistent with our baseline panel local projections specification, we control for four lags of the dependent variable, four lags of the shock, four lags of the interaction term, and the relative level of climate change exposure. In the specifications without time fixed effects, we additionally control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

Figure 14 shows how the response of investment and R&D expenditure 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 1.1 percent decline in investment after two years and an additional 0.5 percent reduction in R&D expenses after one year. Thus, firms experience sharper declines in investment and R&D expenses when their exposure to climate change is higher. Our findings remain robust when we exclude time fixed effects or include more stringent sector-by-time fixed effects.

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. Some sectors may even benefit from higher climate policy uncertainty while others are adversely affected. To assess this, we estimate the panel local projection specification from Equation (9) separately for different

sectors. In particular, we separate the mining, quarrying, oil and gas extraction, and utilities sectors, which may be distinctively affected by climate policy uncertainty, from all other sectors.

Figure 15: Heterogeneous effects based on sector



Notes: Heterogeneous response of investment and R&D expenses to a climate policy uncertainty shock by sector, estimated by sector-specific panel local projections (9) on the aggregated climate policy shock extracted from our baseline external instruments VAR. All variables are converted to real terms using the deflator series. Solid lines represent point estimates, while the dark and light shaded areas indicate 68 and 90 percent confidence bands, respectively. Standard errors are clustered by time, following Almuzara and Sancibrián (2024).

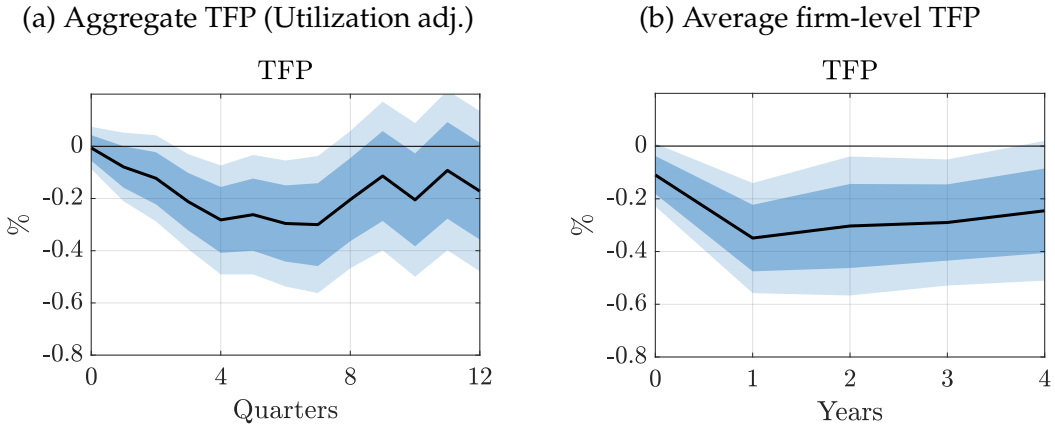
Figure 15 presents the average investment and R&D expenses response to climate policy uncertainty by two groups of sectors. Most sectors display a significant decline in investment and R&D expenses following a climate policy uncertainty shock, with responses quantitatively similar to the overall average in many cases (see appendix Figure D.10 for a more detailed breakdown), which is why we group them together in Panel a. Only the mining, quarrying, oil and gas extraction, and utilities sectors, reported in Panel b, stand out, where investment actually increases accompanied by a substantial decline in R&D expenses. This suggests that climate policy uncertainty drives higher investment in fossil

fuel-related sectors, likely by accelerating brown projects before stricter regulations are enacted, but reduces R&D expenses that spur the green transition. 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 seen that uncertainty about climate policy leads to a marked decline in investment and research and development. This may lead to longer-term consequences for economic productivity more broadly. Firms facing uncertain regulatory environments may delay or scale back investments in innovation, even beyond sectors where climate policies directly alter future profitability. This hesitation can lead to a slowdown in technological progress, reducing productivity growth. Moreover, policy uncertainty can distort resource allocation by leading to overinvestment 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 misallocation of capital comes at the expense of more innovative or lower-emission firms that may be better positioned for long-run growth, further weighing down on aggregate productivity. These channels suggest that uncertainty around climate policy could have lasting negative effects on economic performance.

Figure 16: Climate policy uncertainty and TFP



Notes: Impulse responses of aggregate and average firm-level TFP to a climate policy uncertainty shock, estimated by local projections on the aggregated climate policy 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.

Empirically, we find strong evidence that TFP declines persistently in response to climate policy uncertainty, supporting this interpretation. Figure 16a shows the impulse responses of total factor productivity (TFP) in utility adjusted terms 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. Based on the annual Compustat data, we compute a TFP measure at firm-level as the Solow residual. We find that climate policy uncertainty causes a marked and very persistent fall in firm-level TFP on average, as shown in Figure 16b. Overall, these findings reinforce the view that uncertainty-driven reductions in R&D and capital misallocation have enduring macroeconomic consequences, lowering aggregate productivity.

6. Conclusion

Our analysis uncovers the profound macroeconomic impacts of uncertainty about climate policy. Using a novel measure of climate policy uncertainty, we document its distinct role as a driver of economic fluctuations, operating primarily through supply-side channels. Using an instrumental variable based on major climate policy events, we show that an increase climate policy uncertainty leads to reduced industrial production, GDP, and private investment, while unemployment and prices rise. These findings highlight the distinct transmission mechanism of climate policy uncertainty shocks, which contrasts sharply with the effects of other policy uncertainty shocks that typically propagate more through aggregate demand.

The adverse economic effects weigh down on aggregate emissions, but this comes at a substantial economic cost. Indeed, the emissions intensity remains largely unchanged. At the disaggregated level, we find evidence of a green paradox: investment increases in fossil-related sectors such as mining, oil, and utilities after an increase in climate policy uncertainty. This points to potential longer-term economic costs of climate policy uncertainty through misallocative forces.

Our results have important implications for policymakers. First, they emphasize the economic costs of unclear and unpredictable climate policy. Reducing uncertainty and providing a stable and predictable regulatory environment are crucial to minimizing disruptions during the transition to a greener economy. Second, the findings reveal a nuanced role for monetary policy. While traditional policy uncertainty shocks call for accommodative monetary responses, the supply-side nature of climate policy uncertainty shocks complicates this approach. Careful calibration of monetary policy is essential

to manage the trade-offs between stabilizing output and controlling inflation along the green transition. Overall, our findings highlight the importance of clear, consistent, and forward-looking climate policies to address the dual challenges of mitigating climate change and ensuring economic stability.

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Online Appendix

The Macroeconomic Effects of Climate Policy Uncertainty

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A. Climate policy uncertainty indices

In this appendix, we provide a description of the method used to construct the climate policy uncertainty indices. Broadly, this method involves specifying dictionaries for the concepts "climate change", "policy" (or "climate policy"), and "uncertainty" and identifying articles that contain expressions from all three dictionaries.

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 news. 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*, *Carbon Control News*, and *Washington Week (Energy)*, accessed through *Factiva* news archives. These agencies provide nationwide coverage of 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 the 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, or climate policy and stopping at a generous lower bound[2]. Sometimes, as in previous examples, there are concepts that overlap across the n-grams for a given dictionary, in which case we use the following algorithm.

- *Trigrams:* We start with the trigrams set and work down from the most frequent terms to select the relevant concepts. If the unigram or bigram that comprises a given trigram is *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" in the climate policy concepts since neither

[1] Aruoba and Drechsel (2024) use this method to identify frequently discussed concepts in FOMC announcements.

[2] We manually look through the top 500 unigrams and top 400 bigrams and trigrams.

"cap" nor "trade" are sufficiently specific concepts regarding climate policy. However, for "greenhouse gas emission", we include "greenhouse gas" and "emission" in the 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 the relevant concepts. If the unigram that comprises a given bigram is *not vague in isolation*, we consider including it directly so as to capture all occurrences associated with the term. For example, instead of the bigram "epa administrator", we include the unigram "epa" in the climate policy concepts 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 the relevant concepts, that are *not vague in isolation*.

Finally, we add plurals (and related versions) for the concepts selected into 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 116 concepts, while the *narrow dictionary*, designed to minimize false positives, includes 102 concepts.

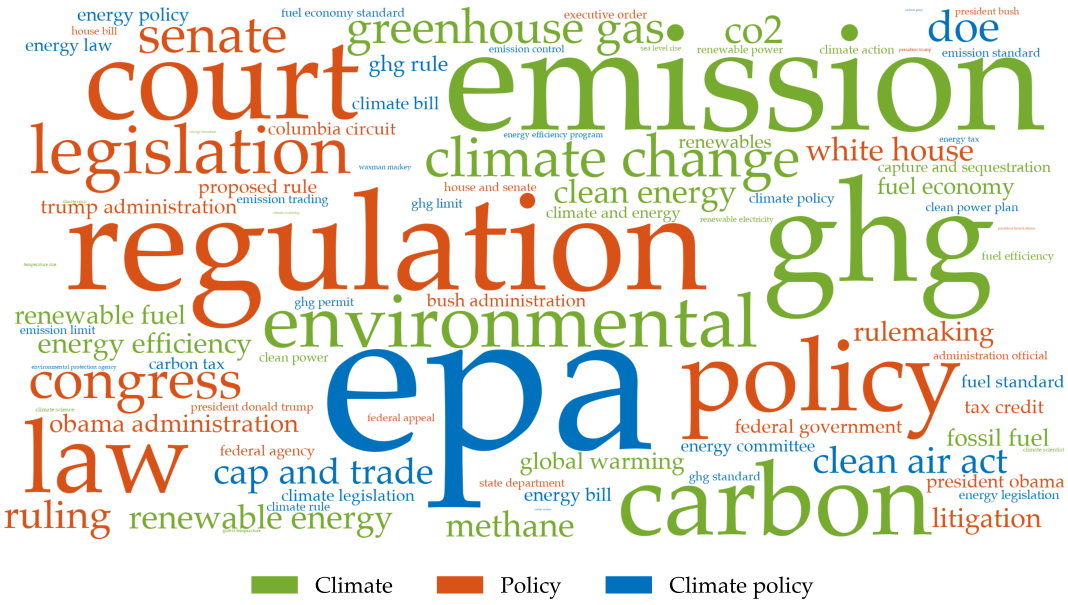
- **Broad dictionary:** The broad dictionary ensures a comprehensive coverage of climate policy concepts, whilst minimizing the likelihood of false negatives. Our algorithm results in the selection of 37 concepts for the climate change dictionary, 41 concepts for the policy dictionary, and 38 concepts for the climate policy dictionary.

- **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 37 concepts for the climate change dictionary, 31 concepts for the policy dictionary, and 34 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.

Figures A.1 and A.2 present the word clouds for the broad and narrow dictionaries, respectively, where the size of the dictionary term represents the frequency of its occurrence across the articles. For example, the broad version includes "carbon", while the narrow version instead includes "carbon capture", "carbon dioxide", "low carbon", and "carbon sequestration". Similarly, the broad version includes "emission", while the narrow version instead includes "carbon emission" and "methane emission".

Figure A.1: Climate policy dictionary: Broad version



By manually imposing these judgmental restrictions on the concepts, we can comprehensively and methodically capture climate policy concepts, while maintaining the interpretability of dictionary-based indices. The specificity of terms in the narrow dictionary reduces the risk of false positives, and is hence our preferred version of the dictionary for the baseline analysis.[4]

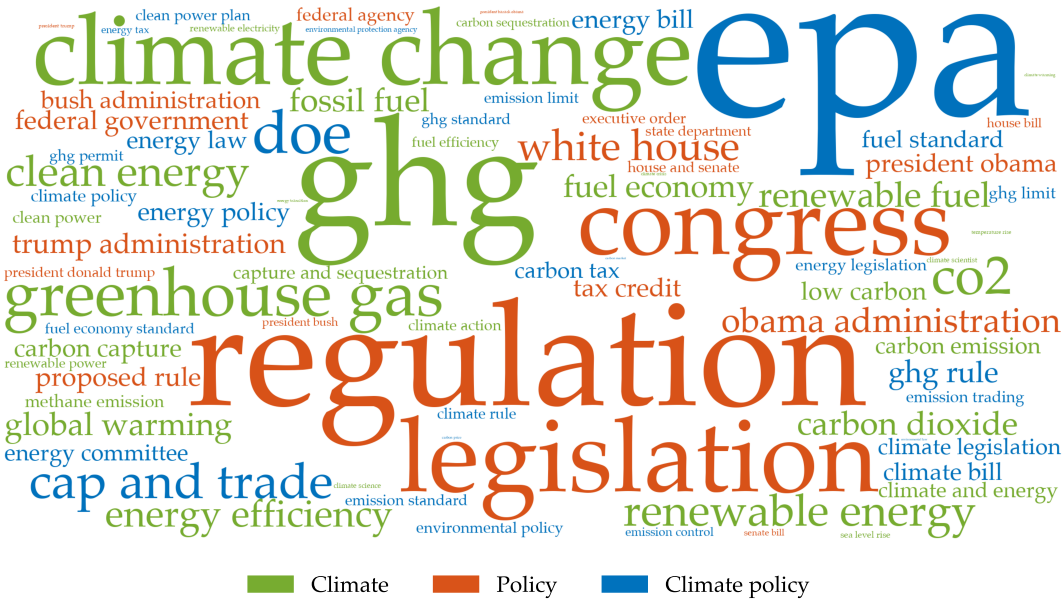
A.2. Constructing the climate policy uncertainty indices

A.2.1. Identifying climate policy uncertainty articles

Our baseline monthly index of climate policy uncertainty is derived from a dataset comprising of 5.46 million news articles published between 1985 and 2025, with an average

[4]The narrow dictionary includes 64 concepts from the climate policy n-gram corpus identified by the algorithm. Additionally, we incorporate 19 concepts from the climate policy n-gram corpus outside the algorithm and 19 concepts external to the corpus to reduce the risk of false negatives.

Figure A.2: Climate policy dictionary: Narrow version



of 10,200 articles per month. These articles are sourced from three leading newspapers—*New York Times*, *Wall Street Journal*, and *Washington Post*—accessed through *ProQuest U.S. Newsstream*.[5] 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. An article is included in this subset if it contains terms from predefined dictionaries, determined by the following search 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 terms 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".

[5]The *New York Times*, *Wall Street Journal*, and *Washington Post* are the three largest newspapers both by print circulation and subscriber count. We also extend our baseline analysis following Baker, Bloom, and Davis (2016) to cover other newspapers—*Boston Globe*, *Chicago Tribune*, *Los Angeles Times*, *Miami Herald*, *San Francisco Chronicle*, and *USA Today*—accessed through *Access World News*.

A.2.2. Constructing the indices

To construct the composite climate policy uncertainty (henceforth, CPU) indices, we use the following steps. First, we scale the number of articles on climate policy uncertainty by the total number of articles in the same newspaper and month. Second, we standardize the series obtained for each newspaper to have a unit standard deviation between 1985 and 2019. Next, we average these series across all newspapers for each month.[6] Finally, we normalize the averaged series to have a mean value of 100 between 1985 and 2019.

A.3. Audit methodology

Alternative news archive. We construct the baseline CPU index using newspaper articles in the *New York Times*, *Wall Street Journal*, and *Washington Post*, accessed through *ProQuest U.S. Newsstream*. As an alternative, we construct the CPU index using newspaper articles in the *Wall Street Journal* and *Washington Post*, accessed instead through the *Factiva* API, giving us access to the full text of articles. The baseline index exhibits a correlation of 0.88 with the *Factiva* index. Additionally, using the same set of newspapers in the baseline index (i.e., excluding *New York Times*) gives us a correlation of 0.92 with the *Factiva* index. The high correlations demonstrate the consistency of the index across different data sources.

Uncertainty dictionary and classification. We augment our uncertainty dictionary with additional terms such as "risk" (and variants "risks", "risked", "risking", "risky", "riskier", "riskiest", and "riskiness"). Additionally, we compute the index using a more stringent criteria to classify CPU articles, requiring that terms from the uncertainty dictionary appear within ten words of terms from the climate policy dictionary.

LLM audit methodology. To evaluate the performance of our baseline index, which is constructed using an automated text-search algorithm, we randomly sample 200 articles from the set of climate policy articles, $\mathcal{B}$. We then use the `gpt-4o-mini` model, accessed through the *OpenAI API*, to identify if an article contains discussions on 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 initial outputs.

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

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. Since we require the full text of the articles, we rely on articles from the *Wall Street Journal* and *Washington Post* procured through Factiva, i.e., a subset of the set $\mathcal{B}$ of climate policy articles. 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 positive rate of our baseline index is below 10%, which is on the lower end of the range typically observed for text-based indices in the literature.

Human audit methodology. To evaluate the performance of the LLM, we use the same 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, which closely align with the prompt given to the LLM:

"We randomly sample 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 book or movie 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)."

B. Instrument for climate policy uncertainty

B.1. Dataset on events with climate policy uncertainty

In this appendix, we provide a detailed list of events identified as leading to climate policy uncertainty. To collect the events, we relied on websites of government administrations, Congress, regulatory agencies, courts, and newspapers. Table B.1 lists the events.

Table B.1: Climate policy uncertainty events

	Date	Event Overview
1	1987-09-16	Montreal Protocol signed by Reagan
2	1988-06-23	Senate testimony by Hansen
3	1989-06-12	Clean Air Act amendments proposed by Bush
4	1990-11-15	Clean Air Act amendments signed by Bush
5	1990-11-16	Global Change Research Act signed by Bush
6	1992-06-12	UN Framework Convention on Climate Change (UNFCCC) signed by Bush at the Rio Earth Summit
7	1992-10-07	UN Framework Convention on Climate Change (UNFCCC) ratified by the Senate
8	1992-10-24	Energy Policy Act of 1992 signed by Bush

Table B.1: Climate policy uncertainty events

	Date	Event Overview
9	1993-02-17	BTU tax proposed by Clinton
10	1993-06-08	BTU tax proposal withdrawn by Clinton
11	1997-07-18	National Ambient Air Quality Standards (NAAQS) revised by EPA
12	1997-07-25	Byrd-Hagel Resolution passed in the Senate
13	1997-10-22	Climate Change Proposal announced by Clinton
14	1997-12-10	Kyoto Protocol agreement announced by Clinton
15	1998-11-12	Kyoto Protocol signed by Clinton
16	1999-01-19	Climate change initiatives announced by Clinton
17	1999-05-14	National Ambient Air Quality Standards (NAAQS) overturned by the U.S. Court of Appeals
18	2000-01-12	Friends of the Earth v. Laidlaw Environmental Services
19	2001-02-27	Whitman v. American Trucking Associations
20	2001-03-13	Kyoto Protocol opposition announced by Bush
21	2002-02-14	Clear Skies Initiative announced by Bush
22	2003-04-22	Waiver of federal preemption for California's Low-Emission Vehicle (LEV II) amendments granted
23	2003-10-30	McCain-Lieberman Climate Stewardship Act blocked in the Senate
24	2005-08-08	Energy Policy Act of 2005 signed by Bush
25	2006-09-20	Lawsuit against automakers filed by California
26	2006-09-27	California's AB32 signed by the Governor
27	2007-01-22	U.S. Climate Action Partnership (USCAP) proposal
28	2007-04-02	Massachusetts v. EPA
29	2007-12-19	Waiver of federal preemption for California's motor vehicle greenhouse gas emission regulations denied
30	2007-12-19	Energy Independence and Security Act signed by Bush
31	2008-06-06	Lieberman-Warner Climate Security Act stalled in the Senate
32	2009-02-17	American Recovery and Reinvestment Act signed by Obama
33	2009-06-26	Waxman-Markey American Clean Energy and Security Act passed in the House
34	2009-06-30	Waiver of federal preemption for California's motor vehicle greenhouse gas emission regulations granted
35	2009-11-17	U.S.-China Clean Energy Initiative announced
36	2009-12-18	Copenhagen Accord reached
37	2010-07-22	Waxman-Markey American Clean Energy and Security Act effectively abandoned in the Senate
38	2010-11-03	Republicans gain House majority in midterm elections
39	2011-03-16	Mercury and Air Toxics Standards (MATS) proposed by EPA
40	2011-06-20	American Electric Power Company v. Connecticut
41	2011-09-02	Implementation of National Ambient Air Quality Standards (NAAQS) for ozone delayed by Obama

Table B.1: Climate policy uncertainty events

	Date	Event Overview
42	2013-06-25	Climate Action Plan announced by Obama
43	2014-04-29	EPA v. EME Homer City Generation, L.P.
44	2014-06-23	UARG v. EPA
45	2014-11-11	U.S.-China climate change announcement
46	2014-11-18	Keystone XL Pipeline bill blocked in the Senate
47	2015-01-25	Arctic National Wildlife Refuge (ANWR) protection proposed by Obama
48	2015-06-29	Michigan v. EPA
49	2015-08-03	Clean Power Plan (CPP) announced by Obama
50	2015-10-01	National Ambient Air Quality Standards (NAAQS) for ozone updated by EPA
51	2015-11-29	Mission Innovation announcement
52	2015-12-12	Paris Climate Agreement reached
53	2016-02-09	Clean Power Plan (CPP) halted by the Supreme Court
54	2016-05-12	Methane emissions rule announced by Obama administration
55	2016-09-09	Offshore Wind Energy Strategy announced by Obama
56	2016-11-09	Trump elected President
57	2016-12-04	Dakota Access Pipeline completion blocked
58	2016-12-07	Scott Pruitt appointed head of EPA
59	2016-12-20	Ban on new offshore drilling issued by Obama
60	2017-01-23	Trans-Pacific Partnership (TPP) withdrawal by Trump
61	2017-01-24	Executive actions to expedite energy and infrastructure projects issued by Trump
62	2017-02-16	Stream Protection Rule repealment signed by Trump
63	2017-03-15	Review of fuel economy and vehicle emissions standards initiated by Trump administration
64	2017-03-28	Energy Independence Policy announced by Trump
65	2017-06-01	Paris Agreement withdrawal by Trump
66	2017-12-07	Greenhouse Gas Endangerment Finding to be reconsidered
67	2018-08-02	Corporate Average Fuel Economy (CAFE) standards rolled back by Trump administration
68	2018-08-21	Affordable Clean Energy (ACE) rule proposed by Trump
69	2018-09-18	Methane waste rule rolled back by Trump administration
70	2019-02-07	Green New Deal (GND) resolution introduced in the Senate and House
71	2019-03-26	Green New Deal (GND) resolution stalled in the Senate
72	2019-09-17	Waiver of federal preemption for California's motor vehicle greenhouse gas emission regulations rejected

The events we identify as contributing to climate policy uncertainty span legislative, regulatory, presidential, and judicial actions. Table B.2 provides a detailed classification of the events identified in Table B.1.

Table B.2: Classification of climate policy uncertainty events

Event Type	Count
Advocacy	**2**
International agreements, treaties, and conventions	**13**
Agreement	4
Announcement	5
Convention ratification	1
Convention signature	1
Treaty signature	2
Judicial action	**10**
Decision	8
Filing	1
Stay order	1
Legislative action	**19**
Blocked, stalled, or withdrawn	6
Introduced	1
Passed — House	1
Passed — Senate	1
Proposed	2
Signed	8
Political event	**3**
Presidential action	**12**
Regulatory action	**13**
Army Corps of Engineers	1
Department of the Interior, Final rule	1
EPA, Announcement	2
EPA, Decision	3
EPA, Final rule	3
EPA, Proposed	3
Total	**72**

B.2. Instrument construction

Event importance. To quantify the importance of each event, we use the information contained in the text of 5.46 million news articles published in the print editions of leading American newspapers, including the *New York Times*, the *Wall Street Journal*, and the *Washington Post*.

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. We classify an article as relating to climate policy if it contains at least one term from each of the climate change and policy dictionaries, or if it contains at least one term term from the climate policy dictionary. We denote this count as $n^{\text{cp}}_{i,d}$, where $i \in \{\text{NYT}, \text{WSJ}, \text{WaPo}\}$ 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 two days following it, i.e., $d \in \{0, 1, 2\}$. This choice balances reducing background noise with allowing sufficient time for news outlets to report on the event. Our results remain robust when using a smaller window, such as only the day of the event ($d \in \{0\}$) or the day of the event plus the following day ($d \in \{0, 1\}$).

Aggregation. To ensure that we account for the variation in the number of articles published in a given newspaper on a given day, we scale the number of climate policy articles by the total number of articles published, $n^{\text{tot}}_{i,d}$. We define the *event intensity* associated with a climate policy uncertainty event, CPU^{Event}_{d}, around a window d, as follows:

$$\text{CPU}^{Event}_{d} = \frac{1}{3} \sum_{i} \sum_{d} \frac{n^{\text{cp}}_{i,d}}{n^{\text{tot}}_{i,d}}$$

Our results are robust to alternative methods of aggregations, such as a cumulative share over the entire window:

$$\text{CPU}^{Event}_{d} = \frac{1}{3} \sum_{i} \frac{\sum_{d} n^{\text{cp}}_{i,d}}{\sum_{d} n^{\text{tot}}_{i,d}},$$

or using the absolute number of climate policy articles:

$$\text{CPU}^{Event}_{d} = \frac{1}{3} \sum_{i} \sum_{d} n^{\text{cp}}_{i,d}.$$

Finally, to obtain the instrument, we aggregate the daily event series to a monthly series

by summing over the normalized counts, CPU_d^{Event}, in a given month. In months with no events, the series takes zero value.

C. Data

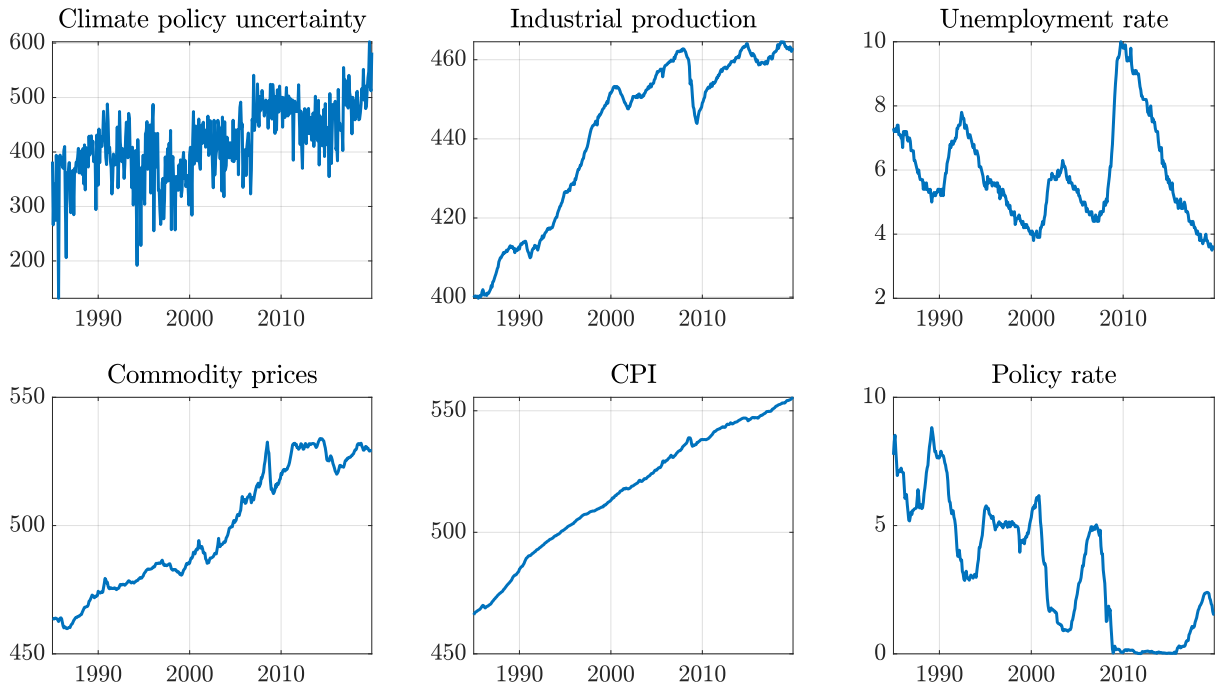
C.1. Macro data

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

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
CP	News-based climate policy news index	ProQuest/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	level
Macro indicators			
INDPRO	Industrial production	FRED	100*log
UNRATE	Unemployment rate	FRED	level
PPIACO	Producer price index all commodities	FRED	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
GDPC1	Real gross domestic product	FRED	100*log
EMISSCO2TOTVTTTOUSA	Total carbon dioxide emissions from all sectors, all fuels	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
UMCSENT	Consumer sentiment, Surveys of Consumers, University of Michigan	FRED	100*log
B358RG3Q086SBEA	Chain-type price index for gross value added (GDP) by non-farm business	FRED	level
TFP_UTIL	Utilization-adjusted TFP	Fernald (2014)	100*log

Figure C.1: Transformed data series in VAR



C.2. Micro data

This appendix provides detailed information on the micro data used in Section 5 of the paper. We describe sources in detail below and also provide an overview of the variables used in the paper 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 use additional filters such as 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 (excluding calendar versus fiscal view). 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. We use the climate change exposure dataset by Sautner et al. (2023), accessed through OSF, to identify firm-level, quarterly climate change exposure 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 CUSIP 6-digit (company/issuer identifier).

Two key points are worth noting here. First, we use the CUSIP 6-digit as an additional identifier variable for the merge since the global company key (gvkey) and calendar year-quarter (datacqtr) do not jointly uniquely identify the observations. We use the CUSIP 6-digit instead of the standard CUSIP 9-digit variable to increase the matches based on the issuing company. Finally, we allow for companies headquartered globally, not just 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, sectoral depreciation rates. Fixed assets comprise of three components: private equipment, structures, and intellectual property products, with differing depreciation rates. Following Ottonello and Winberry (2020), for each sector, we divide the current-cost depreciation of each fixed asset component by the current-cost net stock of the respective component to obtain component-wise depreciation rates. Next, to obtain a sectoral depreciation rate, we take a weighted average of the component depreciation rates, using the net stock share of each component as weights. Finally, we convert the annual depreciation rate to a quarterly rate, assuming equal compounding across the four quarters. Note that while the BEA publishes implied depreciation rates, they are unavailable for NAICS 2-digit codes (sectors), which is the level of NAICS code available for several firms in the Compustat data. Hence, we use above procedure to construct depreciation rates at the NAICS 2-digit codes.

Table C.2: Micro data description

Variable Name	Variable Codes	Calculations
Acquisition ratio	`aqc`: Acquisitions, year-to-date `atq`: Assets, total	Δ `aqc` / `atq` Note that we difference within the firm for a given fiscal year and fiscal year-end month to obtain quarterly values from year-to-date values.
Capital	`ppegtq`: Property, plant, and equipment (gross) `ppentq`: Property, plant, and equipment (net) δ: Depreciation rate, quarterly (computed from BEA data)	We calculate end-of-period capital using the perpetual inventory method, following Ottonello and Winberry (2020). First, we estimate missing observations of `ppentq` using linear interpolation based on the values immediately before and after the missing observation (using the calendar view). If two or more consecutive observations are missing, we do not impute any values. We then compute net investment ($I_{it} - \delta K_{it-1}$) as the change in the interpolated `ppentq`. Next, for each firm, we set the initial value of capital (K_{i0}) to the level of `ppegtq`. Finally, we compute the evolution of capital by adding the changes in net investment to the initial value of capital.
Investment	`capxy`: Capital expenditures, year-to-date	We linearly inter/extrapolate within the firm for a given fiscal year and fiscal year end month. Note that we condition on the fiscal year-end month to account for cases when the firm changes their fiscal year-end month. Next, we difference within the firm for a given fiscal year and fiscal year-end month 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)	
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	(`dlcq` + `dlttq`)/`atq`
Sales	`saleq`: Sales/turnover (net)	
TFP	`saley`: Sales/turnover (net), year-to-date `capital`: Capital, as computed above `emp`: Employees	Residual of the 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 sample period for the firm-level analysis to span from 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. 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 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 particular, we investigate the forecastability of the instrument as well as the relation to other shocks from the literature. The results are shown in Tables D.1-D.2.

Table D.1: Granger causality tests

Variable	**p-value**
Instrument	0.1977
Industrial production	0.1643
Unemployment rate	0.9008
Commodity prices	0.5761
CPI	0.7375
Policy rate	0.9762
Economic policy uncertainty	0.4132
Trade policy uncertainty	0.5255
Geopolitical risk	0.7883
VXO	0.9294
Climate policy news	0.5455
Joint	0.6967

Notes: This table shows the p-values of a series of Granger causality tests of the climate policy uncertainty instrument using 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.

Table D.2: Correlation with other shock series

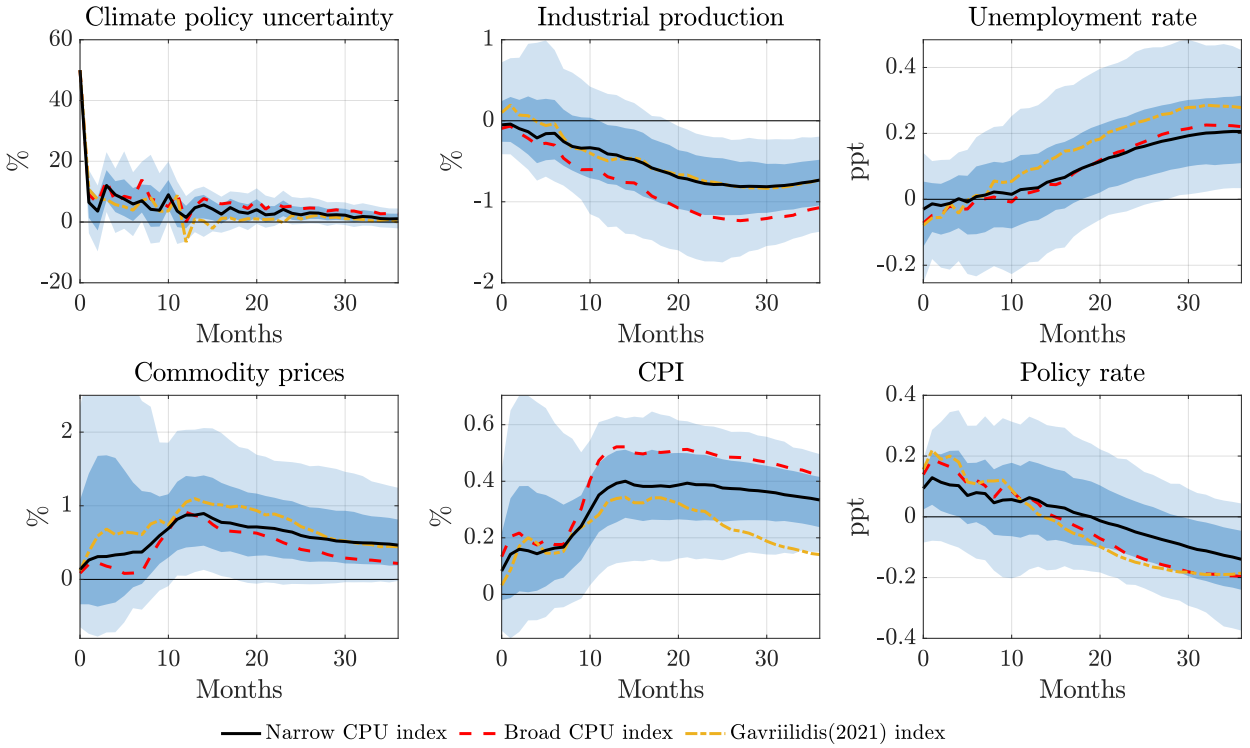
Shock	Source	ρ	p-value	n	Sample
Panel A: Uncertainty shocks					
Uncertainty	Bloom, 2009	-0.07	0.17	384	1986M01-2017M12
	Baker, Bloom, and Davis, 2016	0.08	0.10	384	1986M01-2017M12
	Piffer and Podstawski, 2017	-0.01	0.81	355	1986M01-2015M07
Panel B: Oil shocks					
Oil price	Hamilton, 2003	-0.07	0.20	384	1986M01-2017M12
Oil supply	Kilian, 2008	0.09	0.20	225	1986M01-2004M09
	Caldara, Cavallo, and Iacoviello, 2019	0.00	0.97	360	1986M01-2015M12
	Baumeister and Hamilton, 2019	-0.04	0.37	408	1986M01-2019M12
	Kilian, 2009	-0.03	0.62	264	1986M01-2007M12
Global demand	Kilian, 2009	-0.05	0.46	264	1986M01-2007M12
Oil-specific demand	Kilian, 2009	-0.07	0.29	264	1986M01-2007M12
Oil supply news	Känzig, 2021	-0.06	0.23	408	1986M01-2019M12
Panel C: Productivity and news shocks					
Productivity	Basu, Fernald, and Kimball, 2006	-0.11	0.27	104	1986Q1-2011Q4
News	Barsky and Sims, 2011	0.00	0.98	87	1986Q1-2007Q3
	Kurmann and Otrok, 2013	-0.02	0.86	78	1986Q1-2005Q2
	Beaudry and Portier, 2014	0.03	0.74	107	1986Q1-2012Q3
Panel D: Monetary policy					
Monetary policy	Bauer and Swanson, 2023	0.08	0.14	383	1988M02-2019M12
	Gertler and Karadi, 2015	0.09	0.12	324	1990M01-2016M12
	Romer and Romer, 2004	-0.03	0.70	132	1986M01-1996M12
	Smets and Wouters, 2007	-0.15	0.19	76	1986Q1-2004Q4
Panel E: Financial shocks					
Financial	Gilchrist and Zakrajšek, 2012	0.03	0.60	360	1986M01-2015M12
	Bassett et al., 2014	-0.09	0.44	76	1992Q1-2010Q4
Panel F: Fiscal policy shocks					
Fiscal policy	Romer and Romer, 2010	-0.09	0.40	88	1986Q1-2007Q4
	Ramey, 2011	0.19	0.06	100	1986Q1-2010Q4
	Fisher and Peters, 2010	-0.00	1.00	92	1986Q1-2008Q4

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

Alternative CPU indices. Figure D.1 presents the impulse responses using a selection of different CPU indices: our narrow CPU index (baseline), our broad CPU index (red), and the original index in Gavriilidis (2021).

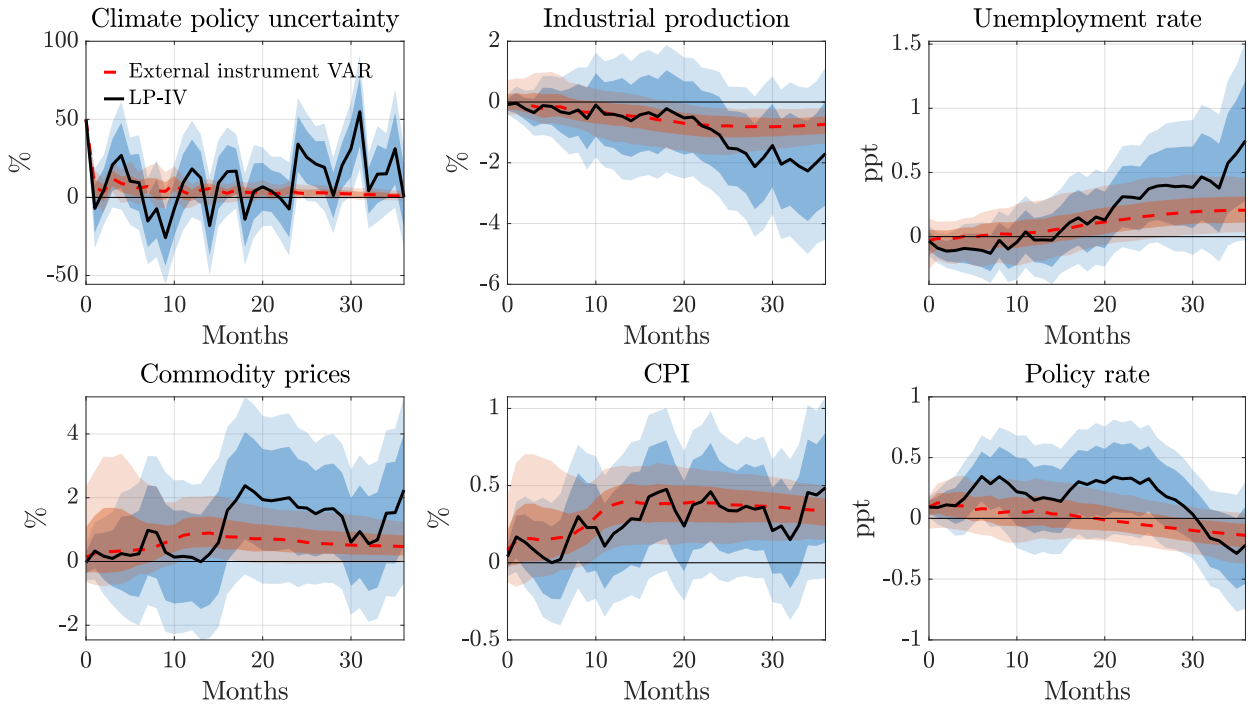
Figure D.1: Impulse responses based on alternative CPU measures



Notes: Impulse responses to a climate policy uncertainty shock estimated using our baseline external instrument VAR using different CPU measures: our narrow CPU index (baseline), our broad CPU index (red), and the initial index in Gavriilidis (2021). The impact response is normalized to increase the respective CPU index by 50 percent. The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for our baseline model with the narrow CPU index.

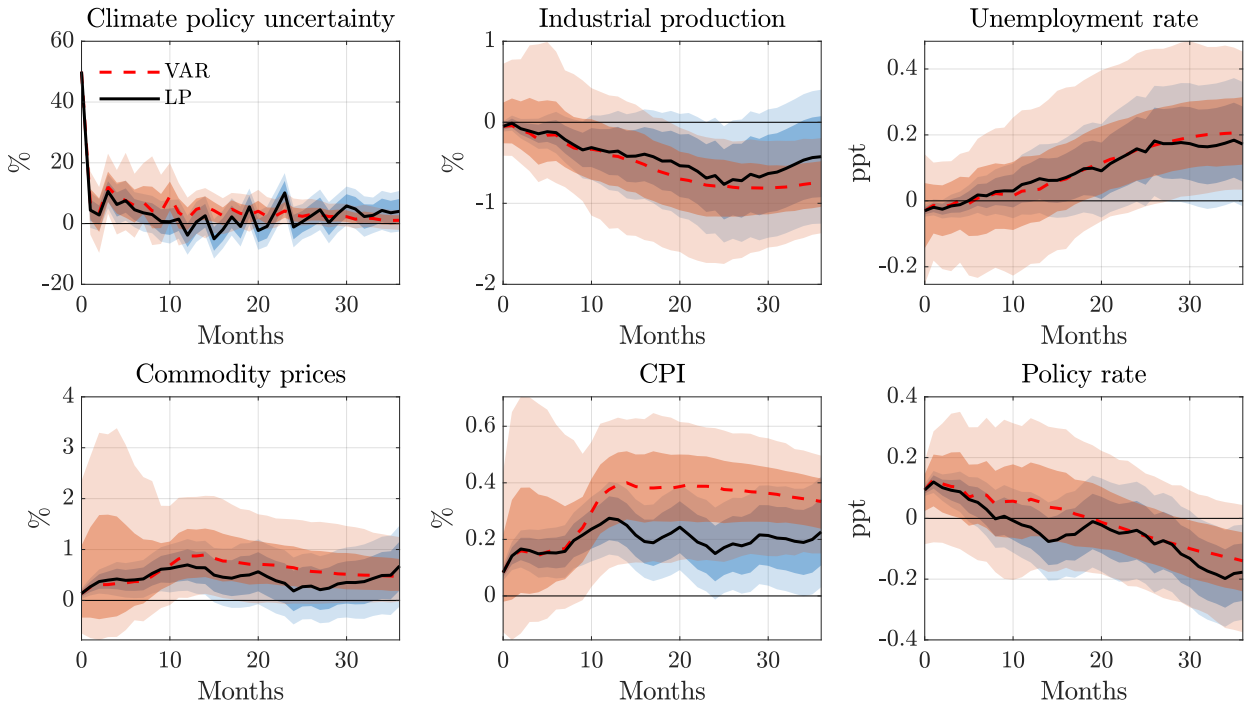
Estimation method. Figures D.2-D.3 show the responses estimated based on local projection specifications.

Figure D.2: Impulse responses to a CPU shock, LP-IV



Notes: Impulse responses to a climate policy uncertainty shock, normalized to increase the CPU index by 50 percent on impact, estimated using LP-IV. The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

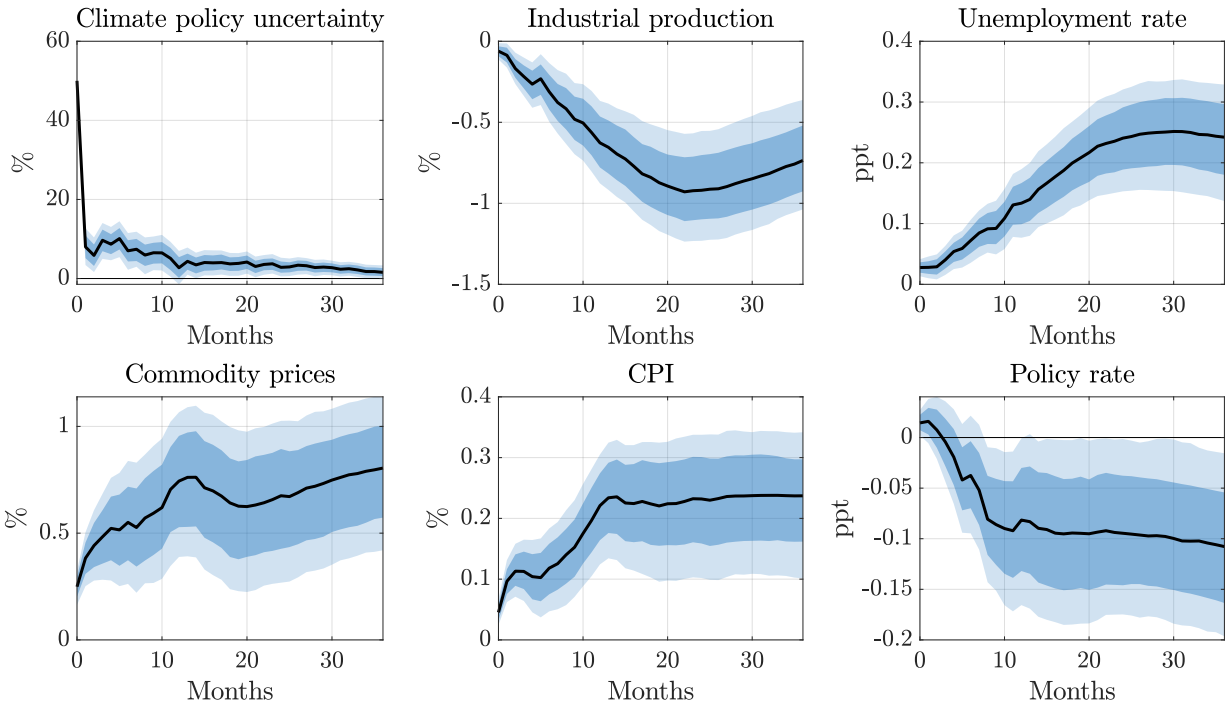
Figure D.3: Impulse responses to a CPU shock, LP on shock



Notes: Impulse responses to a climate policy uncertainty shock, normalized to increase the CPU index by 50 percent on impact, estimated using LP on shock. The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands, respectively.

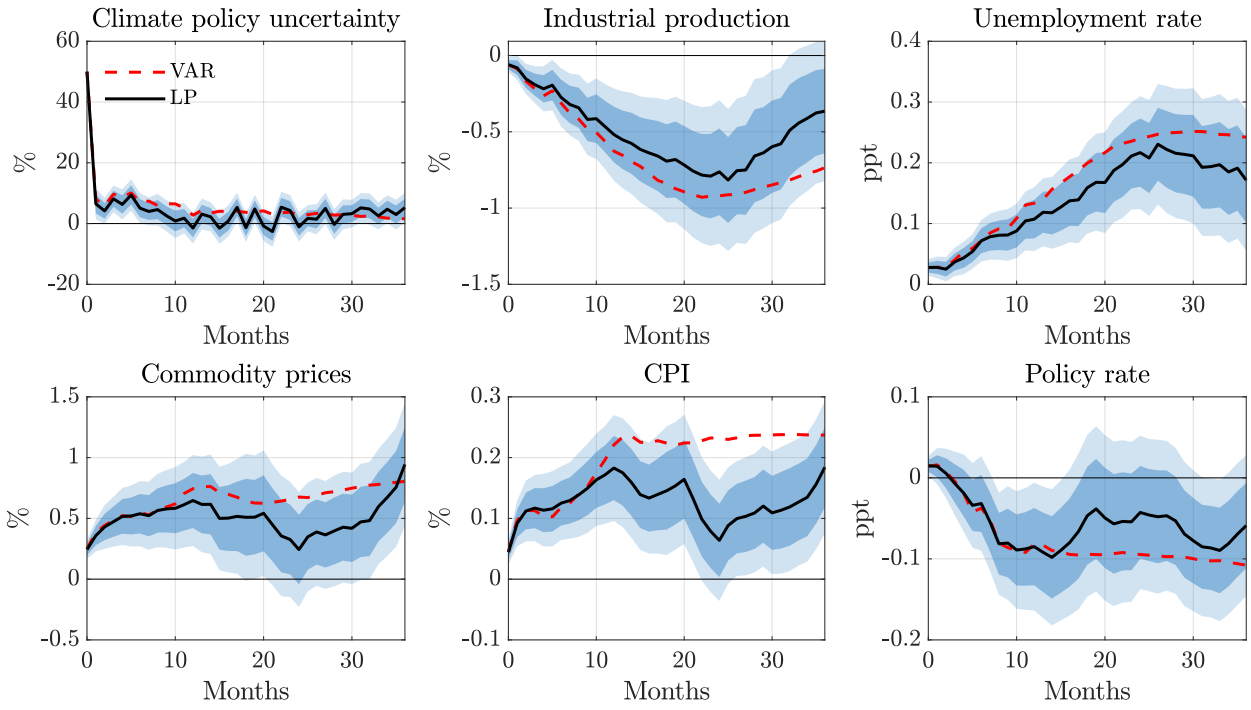
Recursive model. Figure D.4 shows the responses from the recursive VAR, with the CPU index ordered first. This amounts to assuming that the climate policy uncertainty only reacts to macroeconomic developments with a one month lag. We estimate the responses based on the same identifying assumptions using local projections in Figure D.5

Figure D.4: 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 black line is the point estimate and the dark and light blue shaded areas are 68 and 90 percent confidence bands, respectively.

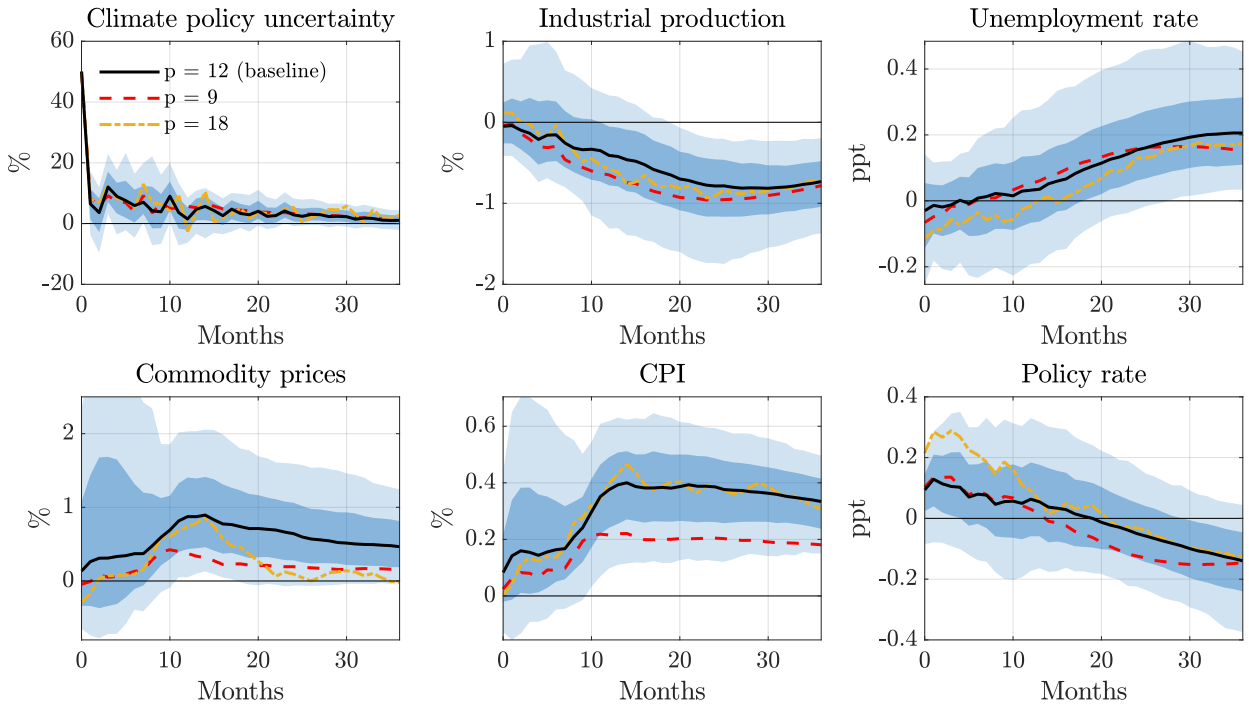
Figure D.5: Impulse responses to a CPU shock, recursive VAR vs. LP



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

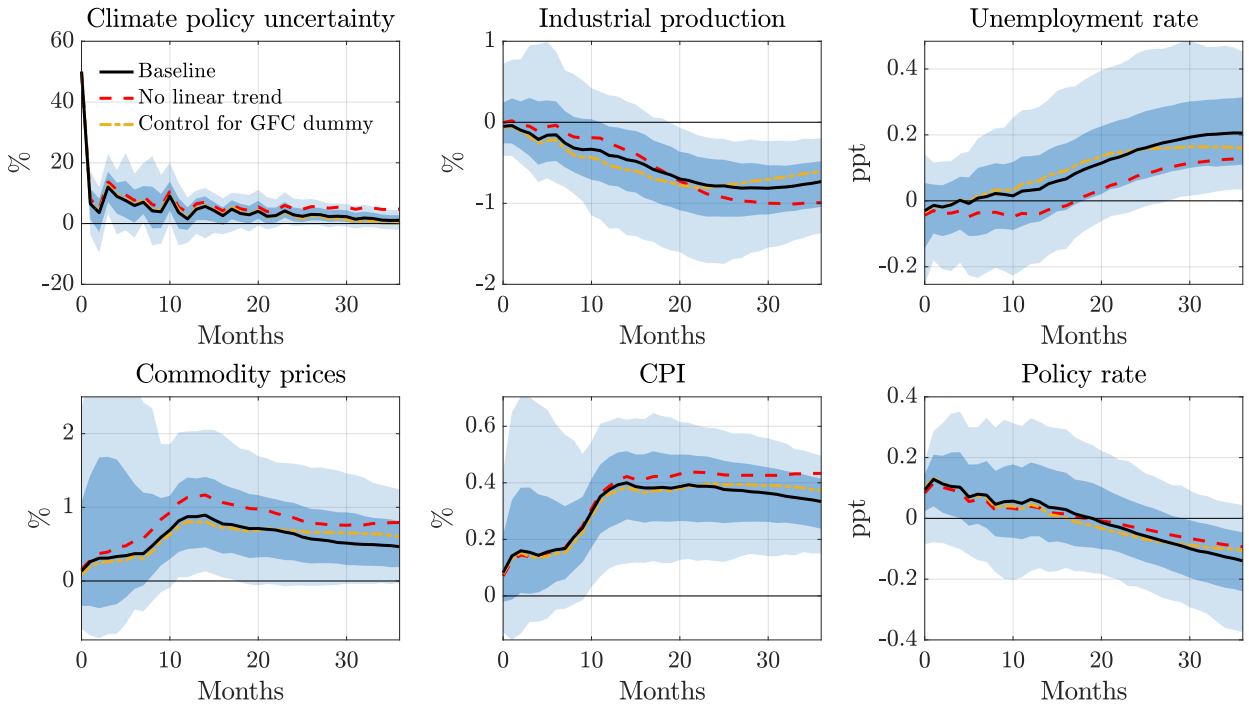
Other specification choices. Figures D.6-D.8 show the results of the sensitivity checks with respect to additional specification choices, including the lag order, deterministics and the specification of the climate policy uncertainty instrument.

Figure D.6: Sensitivity with respect to lag order



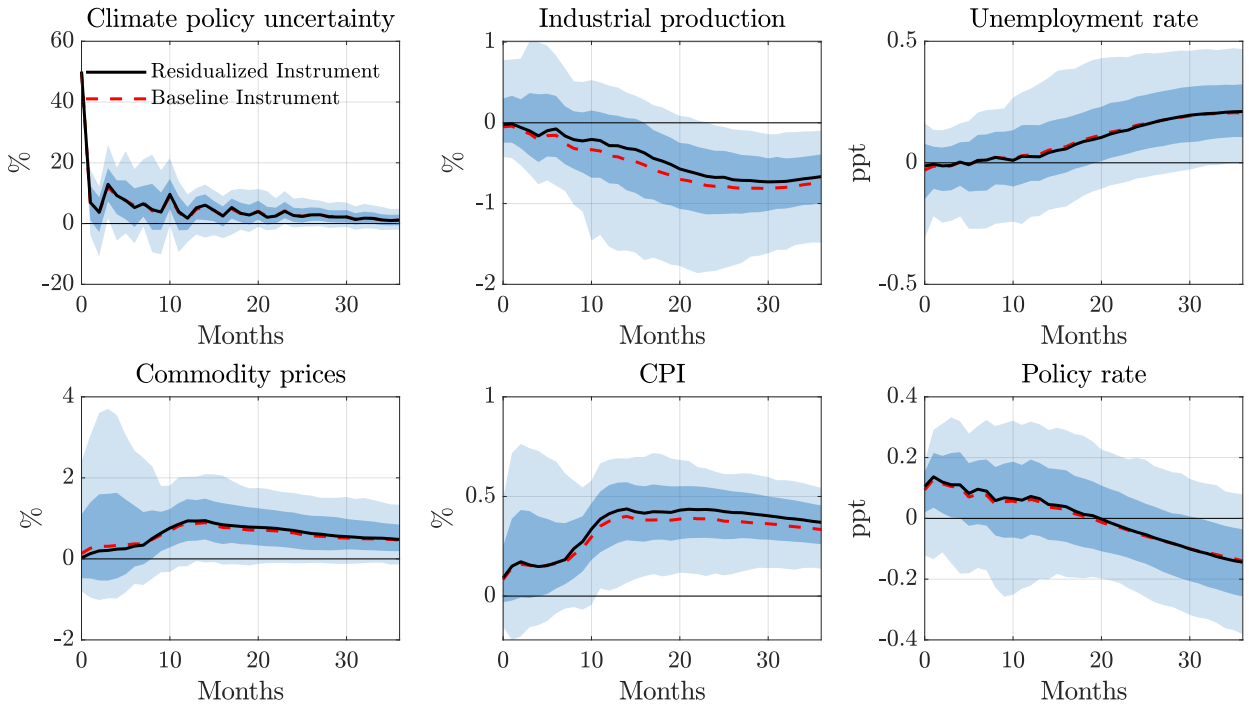
Notes: Impulse responses to a climate policy uncertainty shock estimated using our external instrument VAR with varying lag order. The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands of our baseline model.

Figure D.7: Sensitivity with respect to deterministics



Notes: Impulse responses to a climate policy uncertainty shock estimated using our baseline external instrument VAR compared to a model that excludes the linear trend, and a model that controls for the global financial crisis using a dummy variable. 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.8: Sensitivity with respect to autocorrelation in instrument

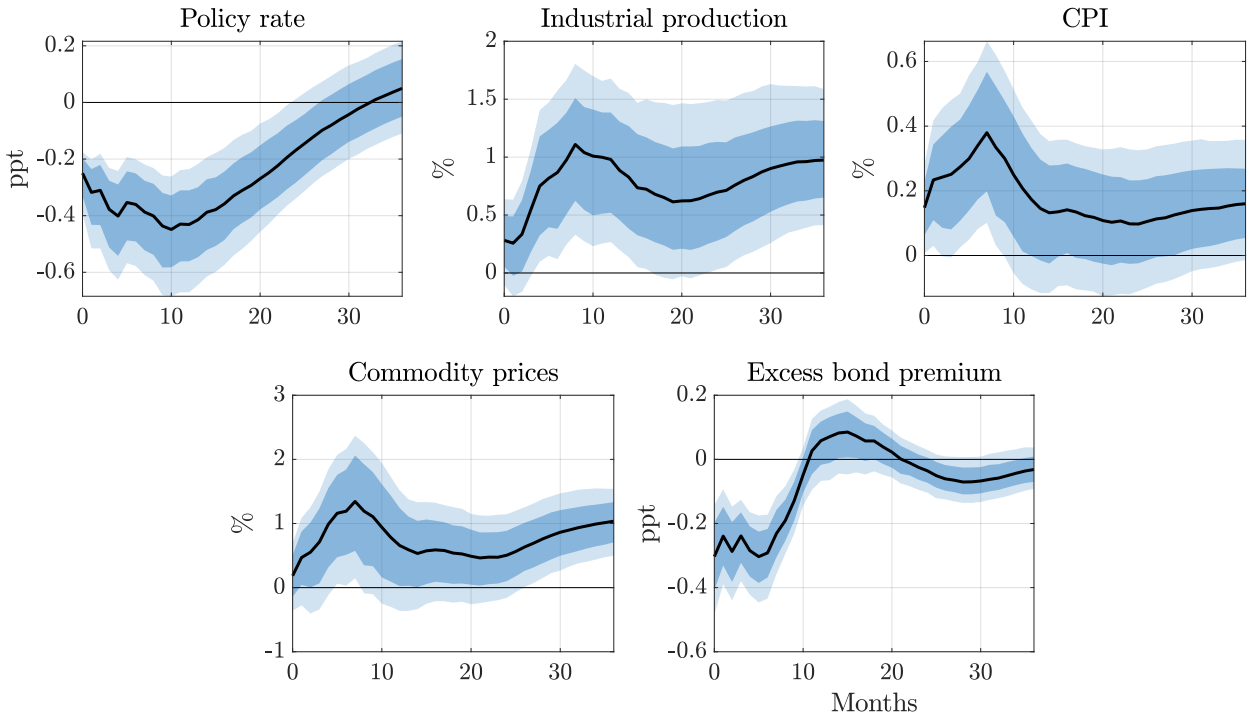


Notes: Impulse responses to a climate policy uncertainty shock estimated using our baseline external instrument VAR compared to a model with a residualized instrument (using 12 lags). The lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands for the residualized instrument model.

Monetary policy VAR. We estimate the impulse responses to a monetary policy shock based on 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 stick as close as possible to our baseline, estimating the model based on the same sample (1985-2019), choosing a lag length of 12 and including a linear trend in terms of deterministics.

The results are shown in Figure D.9. 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 much more persistent and consumer prices increase less persistently. These differences are driven by our shorter sample period.

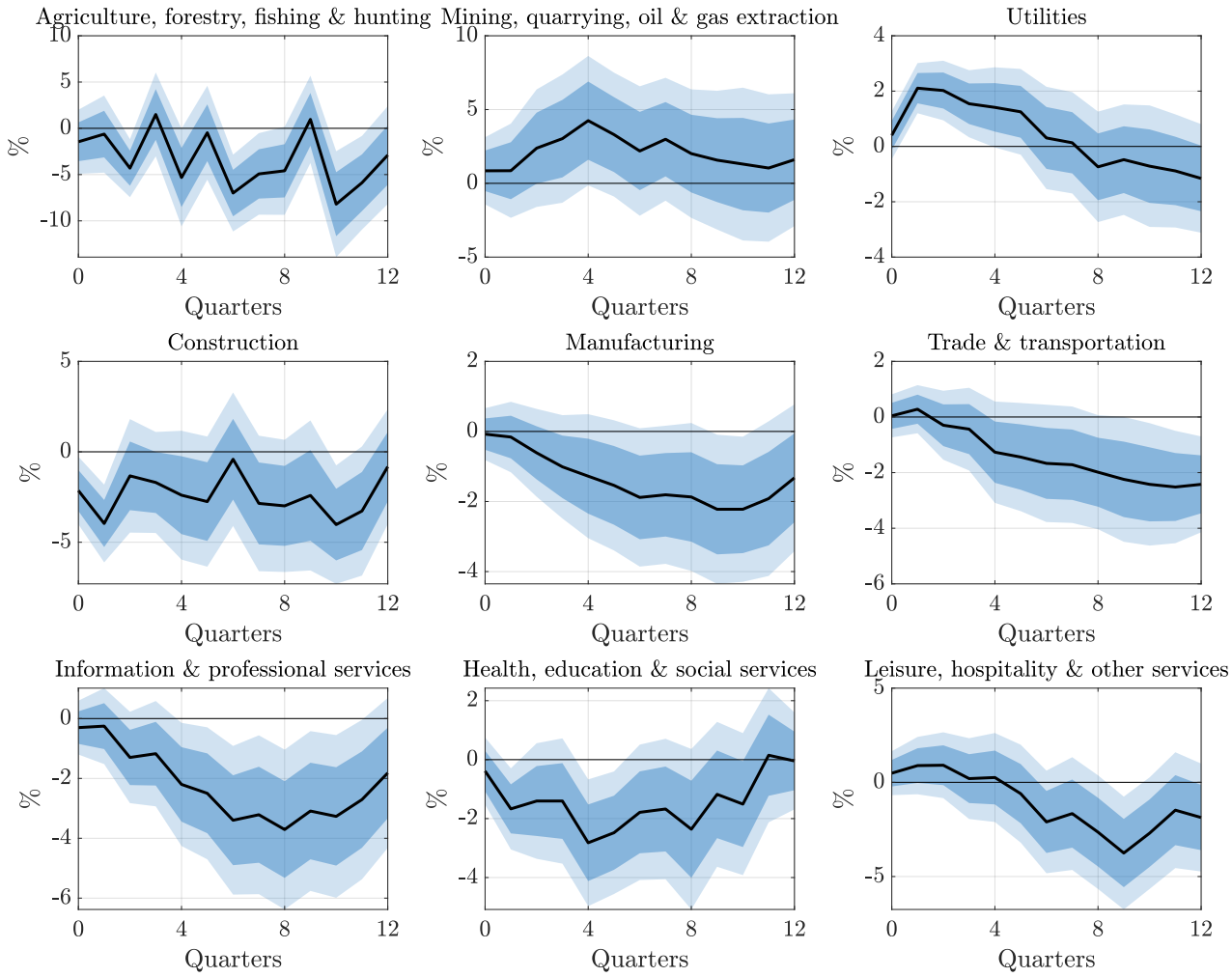
Figure D.9: Impulse responses to a monetary policy shock



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 lines are the point estimates and the dark and light shaded areas are 68 and 90 percent confidence bands.

Sectoral heterogeneity. Figure D.10 shows the average investment response to climate policy uncertainty in the panel across a detailed breakdown of sectors.

Figure D.10: Heterogeneous effects based on sector



Notes: Heterogeneous response of investment to a climate policy uncertainty shock by sector, estimated by sector-specific panel local projections (9) on the aggregated climate policy shock extracted from our baseline external instruments VAR. All variables are converted to real terms using the deflator series. Solid lines represent point estimates, while the dark and light shaded areas indicate 68 and 90 percent confidence bands, respectively. Standard errors are clustered by time, following Almuzara and Sancibrián (2024).

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