DNB Working Paper

No 840/September 2025

Commitment vs Credibility: Macroeconomic Effects of Climate Policy Uncertainty

Fulvia Marotta, Maria Sole Pagliari and Jasper de Winter

DeNederlandscheBank

EUROSYSTEEM

Commitment vs Credibility:Macroeconomic: Effects of Climate Policy Uncertainty

Fulvia Marotta, Maria Sole Pagliari and Jasper de Winter*

* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 840

September 2025

De Nederlandsche Bank NV
P.O. Box 98
1000 AB AMSTERDAM
The Netherlands

Commitment vs Credibility: Macroeconomic Effects of Climate Policy Uncertainty*

Fulvia Marotta† Maria Sole Pagliari‡ Jasper de Winter§

Abstract

This paper introduces a novel media-based index of climate policy uncertainty – the CPU-Concern index – that captures both the prevalence of climate policy uncertainty and the intensity of public concern. Using data from the Netherlands, a setting characterized by ambitious climate targets and persistent credibility challenges, we document how policy announcements shape perceived uncertainty through signaling effects. The CPU-Concern index rises during contested policy debates and declines following formal ratification, with heterogeneous responses depending on the policy's ambition and credibility. We show that climate policy uncertainty primarily transmits through shifts in business and consumer sentiment, affecting stock market prices, investments and real activity. Furthermore, negative CPU shocks generate more persistent economic drag than positive ones, while the opposite holds true for nominal variables, thus highlighting asymmetries in how uncertainty shapes behavior and potential policy reactions. Our findings underscore the importance of credible and transparent policy communication in reducing uncertainty and supporting the low-carbon transition.

JEL Classification: Q54, Q58, E66, D84, E32, C43
Keywords: Climate policy uncertainty, text-based measures, policy signaling, media-based indicators, expectation formation, macroeconomic effects

*The authors would like to thank Sam Fankhauser, Kostas Mavromatis, Leonardo Melosi and participants at the 9th conference on Econometric Models of Climate Change (EMCC), the Brunel University Conference on "Social and Sustainable Finance: Bridging Methods, Policy and Practice" as well as seminar participants at DNB and the Deutsche Bundesbank for useful comments and suggestions. The views expressed in this paper are those of the authors only and should not be attributed to De Nederlandsche Bank or the ESCB.

†De Nederlandsche Bank & University of Oxford, e-mail: fulvia.marotta@ouce.ac.uk

‡De Nederlandsche Bank & Universiteit van Amsterdam, e-mail: m.s.pagliari@dnb.nl

§De Nederlandsche Bank., e-mail: j.m.de.winter@dnb.nl

1 Introduction

Climate policy uncertainty is increasingly recognized as a crucial factor influencing economic decision-making and investment in green technologies. As governments worldwide set ambitious targets for emissions reductions and the transition to a low-carbon economy, the credibility and consistency of these commitments play a vital role in shaping agents' expectations and behavior. Defined by Campiglio et al. (2024) as arising from "misalignments between announced climate targets and actual policy actions", climate policy uncertainty affects agents' expectations about future carbon prices and their broader economic environment. Often, agents rely on policymakers' public commitments, like net-zero pledges, as key signals of future policy direction. However, these announcements influence behavior only if they are viewed as credible and likely to be followed by concrete actions. A history of policy reversals and unmet commitments can erode this credibility, leading agents to doubt government reliability and hesitate in making low-carbon investments.

This skepticism is further fueled by the high perceived transition risks, where socio-economic costs – including potential unemployment, rising energy prices, and capital stranding – might materialize as economies shift away from carbon-intensive technologies (Campiglio and van der Ploeg, 2002). Such impacts may trigger political backlash, thus compelling policymakers to retreat from ambitious climate goals or provoking policy reversals as newly-elected administrations pursue different directions. Additionally, ambiguities or inconsistencies in climate policies might substantially affect investment choices and shape the overall pathway of the low-carbon transition. These uncertainties make it difficult for firms to commit to long-term investments in clean technologies, as they cannot fully predict whether current policies will remain supportive and stable over time. The climate economics literature has highlighted that uncertainties surrounding future policy implementation can discourage investment in sustainable technologies, as firms are faced with the unpredictability of future costs and market conditions (Helm et al., 2003; Nemet et al., 2017; Fuss et al., 2008; Lemoine, 2017; Fried et al., 2022). These studies underscore that potential policy inconsistency and its socio-economic consequences are a key driver of firms' reluctance to invest, as investment decisions must weigh in immediate risks and possible longer-term shifts in the economic landscape (Battiston et al., 2021; Vona et al., 2018).

Although climate policy uncertainty is widely acknowledged as an important factor shaping economic behavior, it remains relatively under-researched, largely due to the challenges related to its definition and quantification in a consistent manner. Existing approaches often follow the methodology of Baker et al. (2016), who use newspaper-based text indices to quantify economic policy uncertainty. Building on this framework, some studies have applied similar text-based methods to measure climate policy uncertainty.

However, these approaches typically fall short of capturing the more nuanced dimensions of climate policy uncertainty, such as policy credibility, alignment with stated targets, risk of policy reversals, and the socio-economic costs associated with the low-carbon transition(Basaglia et al., 2025).

To address this gap, we develop a novel, media-based measure of climate policy uncertainty – the CPU-Concern index. that captures not only the frequency of uncertainty-related reporting but also the degree of concern, as reflected in the sentiment and tone of media coverage. Drawing on methodologies from the economic policy uncertainty literature (Baker et al., 2016) and recent work on fiscal policy signaling (Melosi et al., 2024), we link policy announcements to media-reported uncertainty in a systematic and dynamic way.

Our approach builds on recent advances such as Basaglia et al. (2025), who construct a U.S. based CPU index using newspaper frequency analysis and demonstrate its significant effects on firm behavior and innovation. While their index captures directional uncertainty and sector-level exposure, we extend this literature by integrating sentiment weighting and legislative timing to capture perceived credibility and concern in the Dutch context

Using this index, we make four main contributions. First, we construct the CPU-Concern index for the Netherlands, providing the first high-frequency, sentiment-weighted measure of climate policy uncertainty grounded in financial media. Second, we show that climate policy uncertainty follows the legislative cycle, rising during political debate and declining after formal ratification, highlighting how institutional processes shape public expectations. Third, we provide new evidence on the signaling effects of climate policy announcements, demonstrating that perceived uncertainty responds not only to policy content but also to its timing, ambition, and credibility. Fourth, we quantify the macroeconomic effects of CPU shocks, showing that they reduce business sentiment, investment, industrial production, and stock valuations.

Importantly, we offer the first direct test of the expectations channel in this context, using counterfactual simulations to isolate the role of forward-looking sentiment. Our results complement recent work showing that uncertainty affects the economy primarily through coordinated expectations (Gambetti et al., 2023). We also document novel asymmetric effects, with negative CPU shocks – defined by the sentiment –weighted tone of media coverage, generating significantly stronger and more persistent macroeconomic impacts than positive ones. This finding is consistent with recent evidence that downside uncertainty, rather than uncertainty per se, drives contractionary responses (Forni et al., 2025), and complements the directional asymmetries documented by Basaglia et al. (2025), who distinguish between uncertainty about policy tightening and weakening.

Together, these findings underscore the economic relevance of climate policy credibility and communication. By integrating media sentiment, legislative timing, and expectation formation, our approach offers a new framework for understanding the costs of credibility gaps, and for designing more effective and predictable policy to support the low-carbon transition.

This paper proceeds as follows. Section 2 reviews the background literature on climate policy uncertainty, with a focus on measurement approaches and economic implications. Section 3 develops the conceptual framework underlying our analysis, highlighting the role of policy credibility, signaling, and expectation formation in shaping climate policy uncertainty. It also illustrates how these dynamics unfold in the Netherlands, a relevant case study due to its ambitious climate targets and persistent implementation gaps. Section 4 presents the construction of the CPU-Concern index and discusses its key properties. Section 5 documents the signaling effects of climate policy announcements on perceived uncertainty. Section 6 quantifies the macroeconomic effects of shocks in climate policy uncertainty as captured by changes in the CPU-Concern index, illustrating counterfactuals and asymmetric effects. Section 7 discusses the policy implications of our results. Section 8 concludes.

2 Literature Review

Government commitments shape expectations, with consequences for investment, consumption, and macroeconomic stability. CPU often arises from misalignment between long-term climate goals and actual policy implementation, generating ambiguity for firms and households navigating the low-carbon transition. In this context, accurately measuring CPU and understanding its macroeconomic transmission channels are essential for designing credible and predictable climate policy.

A leading approach to quantifying CPU builds on the Economic Policy Uncertainty (EPU) index by Baker et al. (2016), which tracks the frequency of keywords related to uncertainty in news media. Applied to climate policy, this method has been used by Gavriilidis (2021) and Berestycki et al. (2022) to construct CPU indices that detect spikes in uncertainty following major policy announcements. While informative, these indices typically lack direct links to specific policy events and do not capture the tone or perceived credibility of policy communication. Our study addresses this gap by combining text-based methods with a detailed mapping of actual climate policy announcements and a sentiment-weighted index. This enables a more nuanced measure of CPU that reflects not just the presence of uncertainty, but also the level of concern it generates in public discourse.

The fiscal policy literature offers further insights into the sources of policy uncertainty. In particular, Melosi et al. (2024) emphasize that markets respond not just to the substance of fiscal announcements, but to their credibility and timing. Their framework distinguishes between different phases of policy signaling, intention, implementation, and revision, and shows that uncertainty often emerges from weak or inconsistent communication across these stages. By adapting this approach to climate policy, we can better understand how perceived gaps between announced targets and follow-through generate CPU. Our measurement strategy draws directly on this insight, tracking media responses to climate policy developments to capture how credibility gaps materialize in public sentiment.

While signaling explains the formation of CPU, the question remains how such uncertainty propagates through the economy. Here, recent macroeconomic research highlights the central role of expectations. Gambetti et al. (2023) show that only “agreed uncertainty”, where agents share beliefs about future risks, affects macroeconomic outcomes, emphasizing that uncertainty must shift coordinated expectations to have real effects. This provides a theoretical rationale for using sentiment and tone in media coverage as a proxy for economy-wide belief formation. Our analysis builds on this insight by directly testing the expectation channel through counterfactual simulations, showing that CPU shocks reduce investment and output primarily by depressing forward-looking sentiment.

Moreover, we show that the effects of CPU are asymmetric: negative CPU shocks, which reflect heightened concern about policy backtracking or inaction, have significantly more persistent and damaging macroeconomic effects than positive ones. This result parallels findings from Forni et al. (2025), who show that downside uncertainty, rather than general variance, is what drives contractionary responses. Together, these studies suggest that the costs of climate policy uncertainty depend not only on its frequency, but on the credibility of its signals and the direction of its perceived risks.

By linking the signaling structure of climate policy to the expectations channel through which uncertainty affects the macroeconomy, our study contributes a new perspective on how policy credibility shapes economic behavior in the transition to a low-carbon economy.

3 Conceptual Framework and the Political Economy of Climate Policy

Climate policy uncertainty stems from the gap between policymakers' announced climate targets and the credibility of their commitment to implement them. In the transition to a low-carbon economy, governments use public announcements, such as emissions reduction goals, legislative proposals, and regulatory plans, to shape expectations and incentivize private sector action. However, when such announcements are perceived as lacking credibility or feasibility, they generate uncertainty that affects firms' investment decisions and economic behavior more broadly.

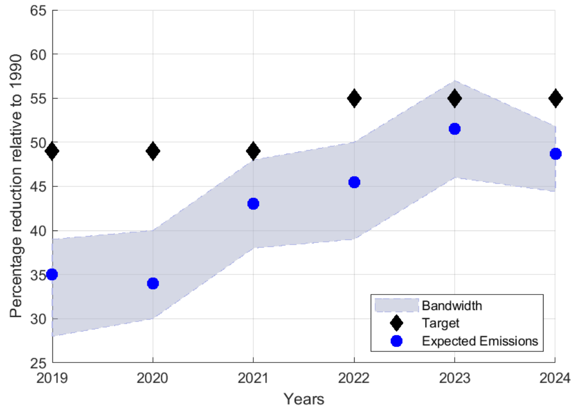
CPU is not static but evolves over time, reflecting the dynamic process through which agents form and revise beliefs about future climate policies. This process is influenced by the sequence of policy announcements, legislative debates, stakeholder consultations, and implementation delays. Uncertainty spikes when new information reveals potential misalignments between targets and actual policies, and gradually declines when credible implementation signals emerge. This framework builds on insights from the fiscal and monetary policy literature, where the credibility and consistency of policy announcements play a central role in shaping expectations (Bernanke et al., 2004; Faust and Svensson, 2001).

The Netherlands provides an ideal setting to analyze the political economy of climate policy uncertainty. Three features make it a particularly instructive case. First, the Dutch government has adopted ambitious climate targets, codified in the Dutch Climate Act, which mandate a 55% reduction in greenhouse gas emissions by 2030 relative to 1990 levels and climate neutrality by 2050. These commitments are reinforced by the National Climate Agreement, a collaborative framework involving businesses, civil society, and government stakeholders. Second, Dutch climate policy operates within a consensus-based political economy, characterized by broad societal engagement but also by structural trade-offs and frictions. Sectors with high emissions, such as agriculture and heavy industry, have successfully lobbied for exemptions or implementation delays, complicating the policy process and contributing to climate policy uncertainty (Van Der Straten et al., 2024). Third, public awareness of climate risks is unusually high, driven by the Netherlands' geographic vulnerability to sea-level rise and other environmental hazards. Climate policy debates receive extensive media attention and are closely followed by the public, amplifying the visibility of policy uncertainty.

Taken together, these factors contribute to create persistent gaps between climate policy announcements and implementation. For example, the government's delay in enforcing emissions-free zones for commercial vehicles extended exemptions for older diesel models, thus disadvantaging firms that had invested early in electric alternatives. Similarly, delays in offshore wind projects and inconsistent renewable energy subsidies have eroded investor confidence. The Netherlands Environmental Assessment Agency (PBL) has highlighted these credibility gaps, projecting only a 5% probability of achieving the 2030 emissions reduction target under current policies (PBL Netherlands Environmental Assessment Agency, 2024). As shown in Figure 1, policy shortfalls reflect a combination of *policy cancellations*, *execution delays*, and *economic changes*, all of which heighten CPU.

This pattern has concrete economic consequences. A consistent history of delayed action

Figure 1: PBL estimates of emission reduction gaps over the years

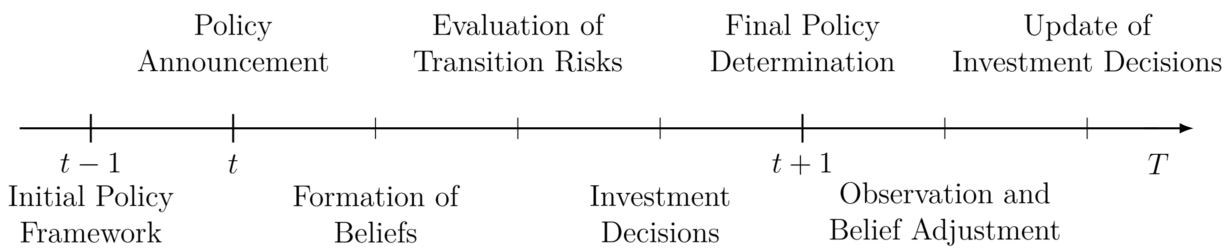


and policy reversals erodes trust in government commitments, increasing the perceived risks and costs of long-term investments in green technologies. As van der Ploeg (2021) emphasizes, stable and predictable policy environments are essential to incentivize private sector action and facilitate a smooth low-carbon transition.

The institutional structure of Dutch climate policymaking contributes to the dynamic nature of CPU. The legislative process is structured but multifaceted, consisting of several stages that introduce uncertainty. Typically, climate policies are drafted by ministries in response to international obligations or scientific recommendations. Public consultations follow, providing stakeholders – including industry and civil society – an opportunity to influence policy design. Parliamentary review further refines the proposal, with the Tweede Kamer (Parliament) debating substantive elements and the Eerste Kamer (Senate) focusing on legal and procedural consistency. After approval by both chambers, the policy is ratified and published, thus signaling formal government commitment.

However, this process introduces uncertainty at each stage. Delays, amendments as well as political contention can generate ambiguity regarding enforcement mechanisms, funding, and long-term consistency. For instance, the roll-out of the Carbon Pricing for Industry law was delayed multiple times, creating ambiguity for firms preparing to adapt to new cost structures. Similarly, the SDE++ subsidy program, designed to stimulate renewable energy investment, faced repeated adjustments and budgetary uncertainties, complicating investment planning.

Section 3 illustrates how CPU evolves over the policy cycle. At $t-1$, firms operate under a stable regulatory environment, forming baseline expectations. At t, the announcement of new climate policy targets triggers a phase of belief formation and heightened uncertainty. During this period, firms evaluate the credibility and feasibility of announced policies, particularly in light of past implementation gaps. Uncertainty peaks during the legislative process, when policy details are debated and subject to change. At $t + 1$, the formal adoption of policies resolves part of this uncertainty, but residual concerns may persist regarding policy enforcement and political commitment.



This framework underscores that CPU is endogenous to the policy process, reflecting the evolving flow of information and credibility signals. For firms and investors, uncertainty arises not merely from the announcement of new targets, but from the perceived likelihood that these targets will be translated into consistent, enforceable policies.

Our conceptual framework builds on a broader literature on policy signaling and credibility. In monetary policy, central banks anchor expectations and reduce uncertainty by providing clear and credible signals about future actions (Bernanke et al., 2004; Faust and Svensson, 2001). However, when commitment is weak or signals are inconsistent, uncertainty increases, with negative effects on investment and economic behavior. This eventually might hinder the very transmission of monetary policy. Similar dynamics apply to climate policy. Governments use policy announcements and legislative frameworks to guide expectations about the future regulatory environment. When these signals are perceived as non-credible or subject to political reversal, climate policy uncertainty rises, affecting firms' expectations and decisions.

In this study, we operationalize this framework in the Dutch context by constructing a novel, media-based index of CPU. The CPU-Concern index captures both the prevalence of uncertainty-related news coverage and the sentiment associated with policy signals. In doing so, we provide an empirical strategy to measure how the credibility and commitment embedded in climate policy announcements influence economic expectations and outcomes.

4 Measuring Climate Policy Uncertainty

Measuring CPU is crucial for understanding how public debate, policy signals, and perceived risks shape economic behavior during the low-carbon transition. Existing indices of CPU, such as those following the methodology of Baker et al. (2016), capture the intensity of media coverage mentioning climate policy and uncertainty-related terms. However, these measures have two key limitations. First, they only capture the prevalence of uncertainty-related news coverage without considering whether this coverage signals a positive or negative context. Second, they are typically normalized relative to total news coverage, which may conflate shifts in climate policy attention with broader media dynamics.

To address these limitations, we develop the CPU-Concern index, a media-based indicator that combines the prevalence of CPU reporting with the degree of public concern reflected in the sentiment and tone of media coverage. Our measure improves on existing approaches in two ways. First, we normalize the index by the total volume of climate policy articles, ensuring that it reflects the share of climate policy discourse associated with uncertainty rather than overall media attention. Second, we integrate a sentiment weighting that captures whether media coverage of uncertainty is perceived as positive, negative, or neutral. This refinement allows us to distinguish between uncertainty arising from constructive policy engagement and uncertainty stemming from policy misalignment, delays, or credibility concerns.

The index is constructed using a comprehensive database of the the leading financial newspaper in the Netherlands, the *Financieele Dagblad* (FD). The database encompasses all articles published in the newspaper (both in print and online) for the period January 1, 1985, to June 30, 2025. The raw database comprises $1,167,101$ articles. The data includes the complete text of each article, the article title, the publication URL, the publication date, the newspaper section in which the article was published, and one or more one-word tags describing the article content. We delete articles that are on human interest, personal profiles and pages in the English language. After the cleaning process, we are left with

765, 160 articles, which is approximately a 35% reduction compared to the raw database.

To construct the baseline CPU-Concern index, we follow the methodology introduced by Baker et al. (2016), which identifies relevant news articles based on keyword filtering. Specifically, we classify an article as discussing CPU if it contains at least one term from each of three categories: i) climate-related terms (e.g., *CO_2*, *climate change*, *renewable energy*), ii) policy-related terms (e.g., *regulation*, *legislation*, *tax*), and iii) uncertainty-related terms (e.g., *uncertain*, *risk*, *unpredictable*). A complete list of translated keywords used for each category is provided in Table A.1 in the Appendix.

On the basis of this filtering, Figure 2 below depicts clouds of the most used words in the groups of articles related to total (Figure 2a) and climate policy (Figure 2b) uncertainty between 2000 and 2025.

Figure 2: Word clouds for total and climate policy uncertainty

(a) Total Uncertainty

(b) Climate Policy Uncertainty

Note: Words dimension is proportional to the frequency of use in news articles. Green words are related to climate, red words are related to policy, blue are all other words.

In the case of total uncertainty, the most prominent terms such as *bank*, *market*, *government*, and *money* highlight concerns centered around macroeconomic and financial stability. This word cloud is also characterized by a dominance of general economic indicators like *inflation*, *interest*, and *investment*, reflecting broader financial and institutional anxieties. In contrast, the climate policy uncertainty cloud features environment-specific terms such as *energy*, *climate*, *green*, and *sustainability*, indicating a strong focus on environmental regulation, energy markets, and policy direction. While both clouds underscore the importance of government and public policy, the climate-focused cloud uniquely blends economic and environmental dimensions, showing how regulatory changes related to climate action contribute to a distinct form of uncertainty.

Against this backdrop, a key refinement that we adopt to construct our CPU-Concern indicator concerns its normalization. While indeed Baker et al. (2016) consider the total number of newspaper articles as denominator of their index, we follow the approach of Noailly et al. (2024) and normalize the measure by the total number of articles that specifically discuss climate policy. This adjustment ensures that our index reflects the prevalence of uncertainty within the climate policy debate itself, rather than its share in overall media coverage. This choice addresses the issue that climate policy reporting has increased substantially over time. Normalizing by total newspaper articles could introduce bias if fluctuations in CPU were driven by general media dynamics rather than genuine changes in policy uncertainty. By anchoring the index to the climate policy coverage, we obtain a more accurate and policy-relevant measure of uncertainty. In Figure A.1 of the Appendix we document the evolution over time of the total number of newspaper articles, the number of climate policy articles, and the number of CPU articles.

A second methodological improvement relates to the temporal aggregation of the index. Whereas existing CPU indices are typically computed at the monthly level, we construct the index at a daily frequency and subsequently aggregate it to the monthly level. This approach allows us to capture short-term fluctuations in CPU that may be overlooked in a framework directly targeting the monthly frequency. The daily index also enables us to detect sudden changes in media coverage in response to specific policy announcements or political events. Meanwhile, aggregating to the monthly level ensures that the index remains consistent with macroeconomic applications and empirical analysis.

While the methodological refinements discussed above improve the precision of the CPU-Concern index, they do not address a fundamental limitation of traditional uncertainty indices: the inability to distinguish between uncertainty that signals risk and uncertainty that signals opportunity. Existing indices, including the baseline CPU-Concern index, measure the frequency of uncertainty-related news coverage but do not capture whether this coverage is perceived positively or negatively. This distinction is particularly relevant in the context of climate policy, where uncertainty may reflect either regulatory instability or growing policy engagement. To address this limitation, we incorporate a sentiment-weighted component into our measure, drawing inspiration from Ardia et al. (2023), who integrate sentiment analysis into a climate change concern index. However, while this represents an important step forward, their methodology does not account for the volume of coverage. A day with 10 articles carries the same weight as a day with 200, even if the topics and tone are similar.

Our methodology builds on both Baker et al. (2016) and Ardia et al. (2023) to construct a sentiment-weighted CPU-Concern index that reflects both the intensity and tone of public concern. Specifically, we: i) use the Baker-style approach to compute the ratio of CPU articles to total climate policy articles (rather than total news articles), ii) weight this ratio by the sentiment of the articles each day, ensuring that uncertainty is adjusted for whether it is perceived as positive or negative, iii) aggregate the daily values into a monthly index, preserving short-term fluctuations while maintaining stability for empirical analysis.

To compute sentiment scores, we use the dictionary developed by Loughran and McDonald (2011), which is tailored to financial news. We translate the list into Dutch and expand it with sentiment terms specific to the Dutch context. We also account for word collocations that reverse sentiment, such as treating "increase" as negative in the phrase "increase in unemployment." The final dictionary includes 1,345 terms, 457 positive and 887 negative words.[1]

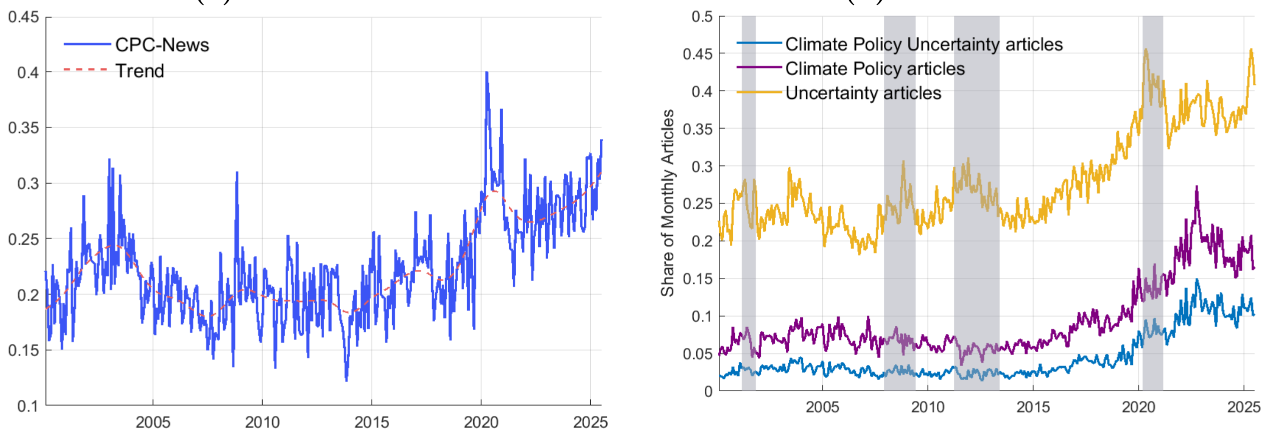
The daily CPU-Concern index is constructed in two steps. First, we compute an article-level *sentiment score* for each news article about climate policy. Let N_t denote the number of climate policy articles published on day t. For each article n published on day t, let $PW_{n,t}$ and $NW_{n,t}$ represent the number of positive and negative words, respectively, and $TW_{n,t}$ the total word count. The sentiment score is defined as:

$$\text{Sentiment}_{n,t} = \frac{1}{2}\left(\frac{NW_{n,t} - PW_{n,t}}{NW_{n,t} + PW_{n,t}} + 1\right). \tag{1}$$

[1] The full list of Dutch sentiment terms is available here.

Figure 3: Evolution of climate policy uncertainty and article shares over time

(a) CPU-Concern **(b)** Articles Share



Note: The left panel displays the monthly CPU-Concern index based on the share of climate policy uncertainty-related articles weighted by sentiment. The right panel shows the share of overall uncertainty articles relative to the total number of articles in *Financieele Dagblad*.

The sentiment score ranges from 0 (very positive) to 1 (very negative), with a score of 0.5 indicating neutral sentiment. This measure can be interpreted as a weighted textual risk metric, where more negative (positive) articles contribute more (less) to the overall concern index.

In the second step, we aggregate article-level sentiment scores into a daily CPU-Concern index. Let TN_t denote the total number of climate policy articles published on day t. The daily CPU-Concern index is defined as:

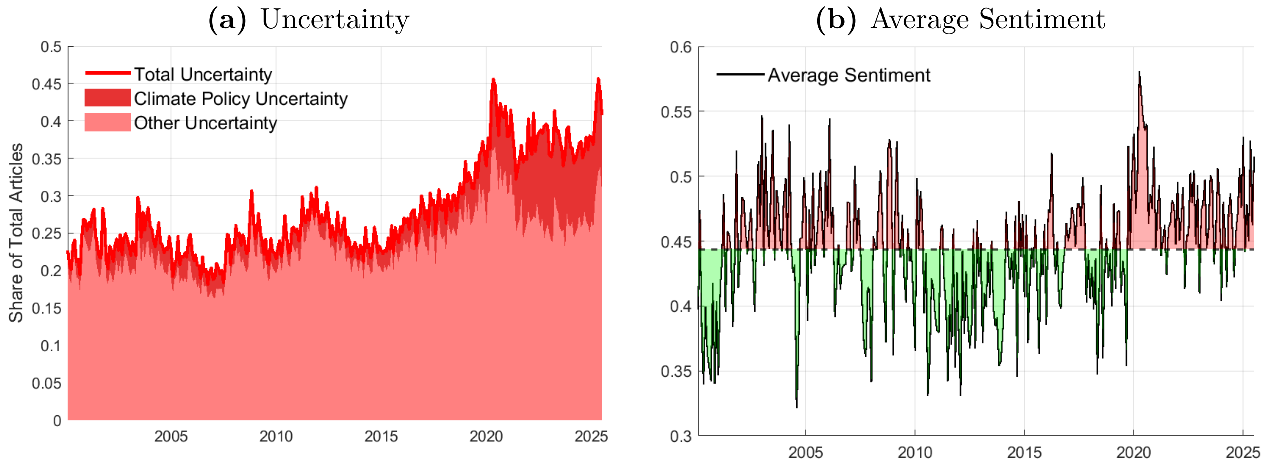
$$\text{CPU-Concern}_t = \underbrace{\frac{N_t}{TN_t}}_{\text{CPU intensity}} \times \underbrace{\frac{1}{N_t}\sum_{n=1}^{N_t} \text{Sentiment}_{n,t}}_{\text{Average sentiment}}. \tag{2}$$

The first term captures the relative prevalence of uncertainty-related articles within overall climate policy coverage, following the Baker-style CPU-Concern index. The second term reflects the average sentiment of uncertainty-related articles on day t. The monthly CPU-Concern index is constructed by averaging the daily index over each month.

The resulting CPU-Concern index thus captures both the intensity and perceived negativity of CPU as reflected in financial media coverage.

To illustrate the properties and dynamics of our index, we depict its evolution over time alongside key patterns in media attention and sentiment. Figure 3 displays two complemen-

Figure 4: Climate policy uncertainty in total uncertainty and associated sentiment



Note: The left panel decomposes total uncertainty into climate policy and other sources. The right panel reports the average sentiment score of CPU articles, scaled between 0 (positive) and 1 (negative). The data indicates an increasing share of climate policy-related uncertainty articles and a predominantly negative framing of CPU in Dutch media since 2015.

tary indicators derived from the index construction. Figure 3a shows the CPU-Concern index, capturing the average monthly share of CPU articles weighted by their sentiment score. The figure reveals a steady increase in media attention to CPU over time, particularly since 2015. Several notable spikes are visible, coinciding with significant climate policy developments in the Netherlands, such as the adoption of the Climate Law (2019), the introduction of the Carbon Levy (2020), and heightened political debate surrounding the climate transition. These peaks reflect moments of increased public and media focus on the risks, costs, and uncertainties associated with climate policies. Figure 3b contextualizes the CPU-Concern index within the broader media information environment. It shows the share of articles related to CPU, overall climate policy, and total uncertainty in the *Financieele Dagblad* over time. The data reveal a gradual but marked increase in the share of CPU articles, particularly since the 2015 Paris Agreement. This is consistent with, among others, Houari et al. (2025) and Frondel et al. (2017). While financial market and macroeconomic uncertainty continue to dominate overall uncertainty coverage, the contribution of CPU has grown substantially in recent years, highlighting their increasing salience in public discourse.

The increasing relevance of CPU is not only quantitative but also qualitative.

Figure 4 presents two additional indicators. Figure 4a decomposes the share of total uncertainty-related articles, distinguishing between climate policy-related uncertainty and other sources. The data reveals that, while total uncertainty has risen steadily since the early 2000s, the share attributable to climate policy has grown particularly fast since 2018. This increase coincides with a period of intensified climate policy activity in the Netherlands, marked by ambitious targets and contentious policy debates. Figure 4b, instead, reports the average sentiment associated with CPU articles. Sentiment is scaled between zero (very positive) and one (very negative), with 0.5 indicating neutral coverage. The figure shows that, over time, the tone of CPU articles has become increasingly negative, particularly from 2015 onward. This trend suggests that media discussions of CPU are framed predominantly in terms of risks, political contention, or economic costs, rather than opportunities or innovation.

These findings highlight two key dynamics. First, CPU has become a distinct and growing component of the broader uncertainty landscape in the Netherlands. Second, media coverage of CPU is increasingly framed in negative terms. Together, these trends suggest that rising public concern over climate policy may create a more cautious environment for long-term investment, as firms and investors internalize both the growing salience and perceived risks of climate policy. These patterns motivate the empirical analysis presented in the following sections.

5 Signaling Effects of Climate Policy Announcements

To further examine whether the CPU-Concern index captures real-world policy discussions, we analyze how media uncertainty evolves around key moments in the legislative process. Section 5 summarizes the major Dutch climate policy laws included in this analysis, alongside their proposal and publication dates. These events mark important milestones where public attention and uncertainty may intensify, thus providing an opportunity to assess whether CPU reacts to concrete policy signals.

Figure 5 presents the cumulative change in CPU around four critical stages of the legislative process: submission of the policy proposal to Parliament, approval by the Parliament (*Tweede Kamer*), approval by the Senate (*Eerste Kamer*), and official publication in the Government Gazette. The figures display cumulative changes in CPU from one day before to five days after each event, across a range of major climate policies, including the Climate Law, the Carbon Levy for Industry, and others.

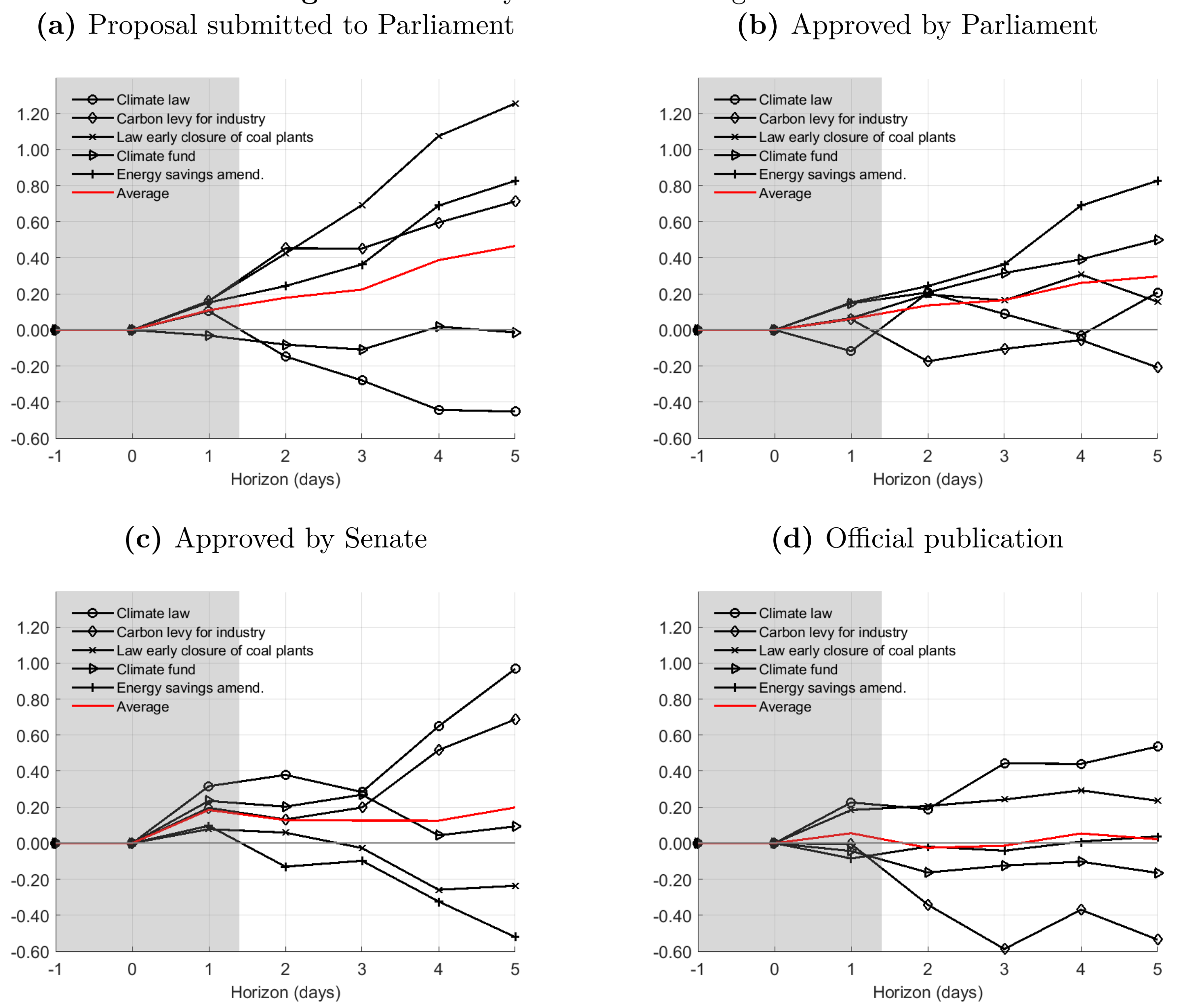
Law	Description	Legislative Process
Climate Law	Establishes binding climate targets: 55% emissions reduction by 2030 and climate neutrality by 2050, with periodic progress monitoring.	12 Sep 2016 – 10 Jul 2019
Carbon Levy for Industry	Introduces a carbon levy on heavy industry to incentivize emissions reduction, with progressively increasing rates.	15 Sep 2020 – 23 Dec 2020
Climate Fund	Creates a dedicated public investment fund to finance climate-related projects, focusing on emissions reduction and renewable energy.	14 Dec 2022 – 01 Feb 2024
Law on Early Closure of Coal Plants	Mandates the early closure of coal-fired power plants to reduce emissions and accelerate the energy transition.	08 Dec 2020 – 26 Jun 2024
Energy Savings Amendment	Updates energy-saving obligations for businesses to strengthen energy efficiency requirements.	11 Apr 2023 – 13 Jun 2023

The patterns reveal a clear dynamic in the evolution of CPU during the legislative cycle. As shown by Figure 5a and Figure 5b, CPU tends to increase sharply around the initial proposal phase, particularly when policies are submitted to Parliament. This reflects heightened media coverage, public debate, and political uncertainty about the scope, timing, and implications of the proposed legislation. The right panel shows that CPU remains elevated, though to a lesser extent, around formal approval by the Parliament.

In contrast, Figure 5c and Figure 5d illustrate that CPU stabilizes or declines during the later ratification stages. Approval by the Senate leads to a flattening of CPU, and the index decreases further after official publication of the law. These dynamics suggest that formal ratification and legal finalization reduce uncertainty, as information about the policy content becomes clearer and more credible.

Overall, the data reveals that the level of CPU is not constant throughout the policy cycle. Instead, it varies systematically across different phases of the legislative process and policy types. Our analysis shows that CPU tends to increase most strongly during the early legislative stages, particularly when policies are sent to Parliament. This phase often coincides with public debate, media scrutiny, political negotiation, and uncertainty about the final form or timing of the law. In contrast, CPU flattens or declines following formal approval by either chamber of Parliament and decreases further after the official publication

Figure 5: CPU dynamics around legislative events



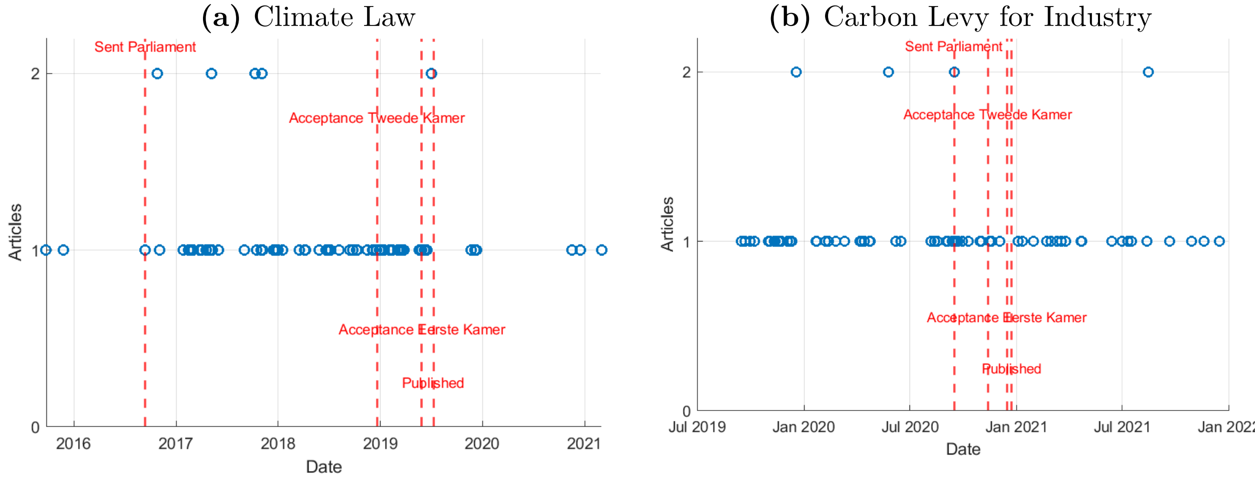
Note: Cumulative change in CPU around four legislative milestones. The red line shows the average change across events. Individual lines correspond to specific policy laws listed in Section 5.

of the law. This pattern is visible across multiple policies – including the Climate Law, the Carbon Levy for Industry, and the Climate Fund – and is reflected in the average CPU response.

These dynamics underscore the importance of institutional credibility: clear, predictable, and legally anchored policy signals reduce uncertainty, while vague or drawn-out legislative processes amplify it. From a policy design perspective, this suggests that uncertainty is not only about the content of climate measures but also about the process by which they are developed and communicated. Accelerating clarity and minimizing ambiguity in early stages could significantly reduce CPU and its potential economic effects.

To provide further descriptive evidence that the CPU-Concern index captures real policy

Figure 6: Timing of media articles around legislative events



Note: Each dot corresponds to an article in *Financieele Dagblad* mentioning either the Climate Law or the Carbon Levy for Industry. Vertical red lines mark key legislative milestones: proposal submission, approval by the Parliament and Senate, and official publication.

discussions, we also examine the timing of media articles relative to key legislative events. Figure 6 shows the distribution of articles in the *Financieele Dagblad* that mention either the Climate Law (Figure 6a) or the Carbon Levy for Industry (Figure 6b), alongside vertical lines indicating legislative milestones.

A comparison between these two cases illustrates how the relationship between media attention and the legislative calendar varies depending on the policy type and political context. For the Climate Law, media attention was concentrated in the early stages of the legislative cycle. Articles mentioning the Climate Law increased shortly after the proposal was submitted to Parliament in 2016 but diminished well before the law was formally approved, despite the long legislative process lasting nearly three years. This pattern suggests that public uncertainty and debate may have peaked early and faded as the legislative process progressed and institutional clarity improved.

By contrast, the Carbon Levy for Industry exhibits a different pattern. Although the formal legislative timeline was relatively short, moving from proposal to publication within a few months, media attention was both earlier and more persistent. Articles referring to the carbon levy appeared well before the policy was formally submitted and remained frequent long after the formal ratification. This sustained attention likely reflects the contentious nature of the policy, with significant implications for industrial competitiveness, economic costs, and stakeholder negotiations.

Importantly, approximately 50% of these articles explicitly mention CPU, indicating that media attention to these laws is not merely descriptive but often framed in terms of uncertainty, credibility, and perceived risk. These two cases underscore that media-reported uncertainty is not confined to formal legislative events, but reflects broader political dynamics and public debate. Some measures – especially those having distributional implications or contested economic consequences – may generate prolonged and intense media attention, thus extending beyond the legislative timeline.

Overall, these descriptive patterns confirm that the CPU-Concern index captures meaningful signals of climate policy debate and legislative activity. The dynamics of the index align closely with the legislative process, rising during phases of political uncertainty and declining once policies are ratified and published. Moreover, the intensity and duration of media attention vary across policies, reflecting differences in economic stakes, political contestation, and public interest.

6 Quantifying the Economic Effects

The previous sections have established that CPU in the Netherlands, as measured by our index, exhibits clear dynamics around key policy events. We have shown that CPU-Concern index tends to increase during early stages of the legislative process, when the content and timing of climate policies remain uncertain, and declines once policies are ratified and published. While these dynamics suggest that CPU reflects meaningful policy debate, an important question remains: does CPU affect economic behavior?

Leveraging on the conceptual framework outlined in Section 3, we treat CPU as an information shock that alters firms' expectations and influences economic outcomes. In particular, the timing and credibility of climate policy announcements can generate fluctuations in uncertainty, affecting firms' investment plans, business sentiment, and financial market valuations. This channel mirrors the well-documented role of credibility and commitment in shaping expectations in the monetary policy literature (Bernanke et al., 2004; Faust and Svensson, 2001).

In this section, we formally quantify the dynamic effects of CPU shocks on key macroeconomic and financial indicators. We estimate a Bayesian Vector Autoregression (BVAR) model to isolate unexpected increases in CPU and trace their impact on business confidence, investment intentions, and stock market valuations. This empirical strategy allows us to assess the extent to which CPU influences the real economy, beyond the descriptive evidence presented in previous sections.

6.1 Data and Empirical Strategy

To investigate the structural relationship between macroeconomic and financial indicators and CPU, we estimate a *monthly* Bayesian Vector Autoregression (BVAR) model including the following endogenous variables in (log) levels: our CPU-Concern index; business confidence taken from Eurostat, measured on the basis of survey responses by Dutch industrial firms; economic sentiment as quantified by the European Commission's Economic Sentiment Indicator (ESI), which aggregates business and consumer expectations across sectors; industrial production (manufacturing) and private non-residential investment data, sourced from Eurostat and CBS, respectively; financial market reactions captured by the Dutch AEX stock market index, obtained from Refinitiv. Investment data are seasonally adjusted using the Census X-13 methodology. The time coverage spans from 2006M6 to 2024M12.

The reduced-form BVAR is then specified as:

$$\boldsymbol{y}_t = \boldsymbol{A}_1\boldsymbol{y}_{t-1} + \boldsymbol{A}_2\boldsymbol{y}_{t-2} + \cdots + \boldsymbol{A}_p\boldsymbol{y}_{t-p} + \boldsymbol{u}_t, \tag{3}$$

where $\boldsymbol{y}_t$ denotes the $n \times 1$ vector of endogenous variables as listed above; $\boldsymbol{A}_i$ $(i = 1, \ldots, p)$ are $n \times n$ coefficient matrices; p is the lag length; and $\boldsymbol{u}_t$ is an $n \times 1$ vector of reduced-form residuals with covariance matrix $\boldsymbol{\Sigma}_u$. Following standard practice, we set $p = 7$ lags to capture temporal dependencies and allow for delayed effects. The BVAR is estimated using a Minnesota prior, which shrinks coefficients toward a random walk process for endogenous variables while allowing for flexibility in short-run dynamics. This prior helps mitigate overfitting concerns in small-sample settings.

To identify structural CPU shocks, we impose a recursive identification scheme, based on the Cholesky decomposition of $\boldsymbol{\Sigma}_u$. Specifically, we assume the following structural form:

$$\boldsymbol{A_0}\boldsymbol{y}_t = \boldsymbol{C}_1\boldsymbol{y}_{t-1} + \cdots + \boldsymbol{C}_p\boldsymbol{y}_{t-p} + \boldsymbol{\varepsilon}_t, \tag{4}$$

where $\boldsymbol{A_0}$ is an $n \times n$ contemporaneous impact matrix, $\boldsymbol{C}_i$ are coefficient matrices, and $\boldsymbol{\varepsilon}_t$ is an $n \times 1$ vector of orthogonal structural shocks, with $\mathbb{E}[\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'] = \boldsymbol{I}_n$. The structural shocks $\boldsymbol{\varepsilon}_t$ are related to the reduced-form residuals as follows:

$$\boldsymbol{u}_t = \boldsymbol{A_0}^{-1}\boldsymbol{\varepsilon}_t. \tag{5}$$

The recursive identification assumes a lower-triangular structure for $\boldsymbol{A_0}^{-1}$, ordering the CPU-Concern index first in the vector $\boldsymbol{y}_t$. This implies that CPU shocks can contemporaneously affect all the other variables, while CPU itself is not contemporaneously impacted by the other shocks. Such ordering reflects the interpretation of CPU as an exogenous information shock, which influences economic expectations and financial variables with a contemporaneous impact. In our baseline setting, we impose this recursive structure to recover impulse response functions (IRFs) to an identified CPU shock. The Minnesota prior is calibrated following standard conventions in the literature, with hyperparameters tuned to balance shrinkage and flexibility. The dynamic responses of the endogenous variables to a standardized CPU shock are traced over a 24-month horizon. This empirical strategy allows us to assess whether unexpected increases in climate policy uncertainty lead to persistent effects on business sentiment, investment intentions, and financial market valuations, while accounting for dynamic feedback and endogeneity.

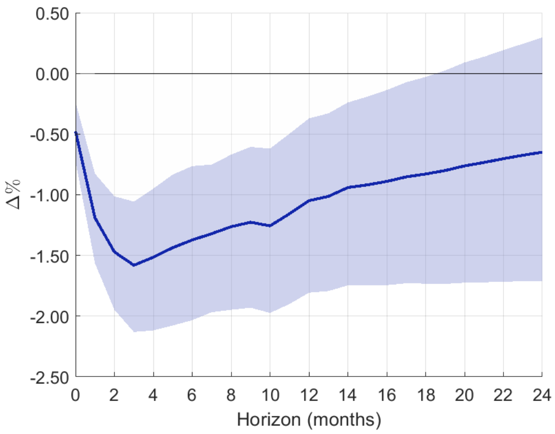
6.2 Results

The conceptual framework outlined in Section 3 suggests that increases in climate policy uncertainty can affect economic expectations and real activity through informational and credibility channels. In this section, we empirically test this hypothesis by estimating the dynamic responses of key economic and financial variables to a standardized CPU shock.

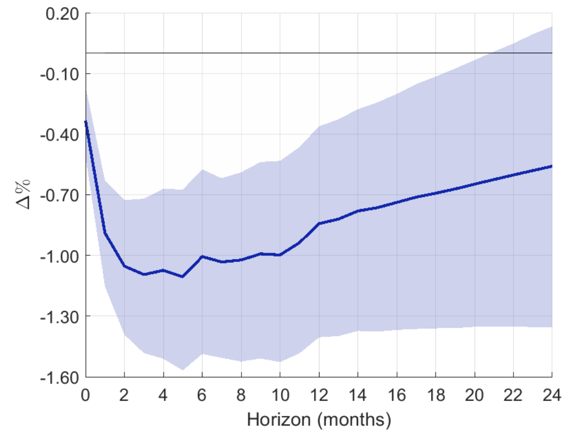
Figure 7 displays the IRFs of the BVAR model described in Section 6.1. Each IRF traces

Figure 7: Impact of climate policy uncertainty shocks on expectations and real activity

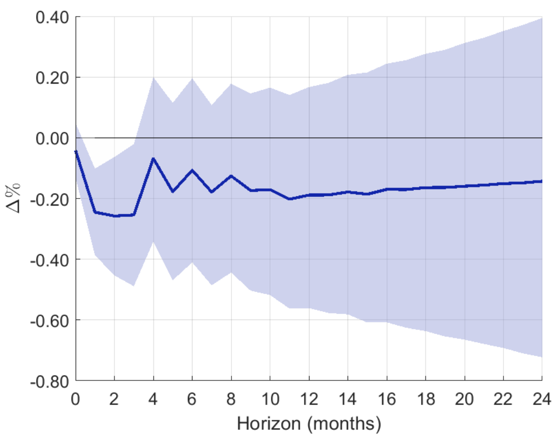
(a) Economic Sentiment



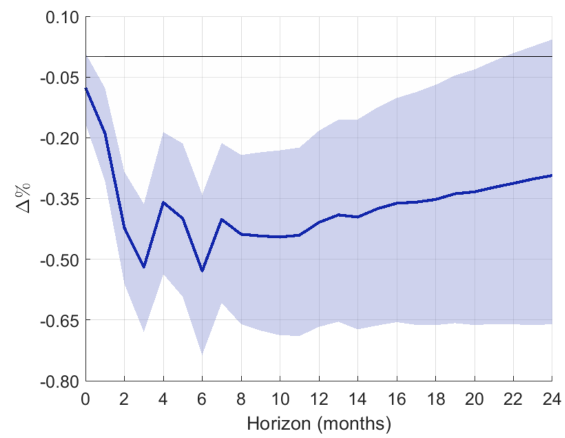
(b) Industrial Confidence



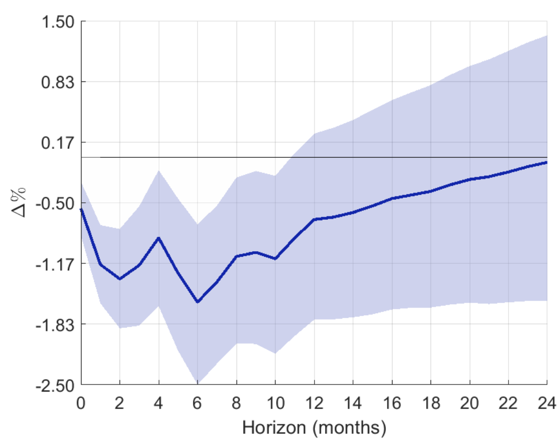
(c) Investment



(d) Industrial Production



(e) Stock Market Index



Note: Impulse response functions (IRFs) to a one-standard-deviation shock to climate policy uncertainty. Shaded areas represent 68% highest posterior density intervals. Variables are expressed in percentage change relative to baseline.

the dynamic effect of a one-standard-deviation CPU shock on business confidence, economic sentiment, private investment, industrial production, and stock market valuations over a 24-month horizon.

Figures 7a and 7b illustrate the response of forward-looking economic indicators to a CPU shock. The Economic Sentiment Indicator decreases significantly, reaching a peak reduction of approximately 1.6% within three months. Industrial confidence exhibits a similar pattern, falling by 1.1% at its trough. Both effects are statistically significant and dissipate within five to six months after the shock.

These results provide empirical support for the expectations channel emphasized in the policy uncertainty literature. Increases in the CPU-Concern index generate short-term declines in business and consumer sentiment, consistent with precautionary behavior in the face of uncertain policy signals. This finding aligns with our conceptual framework, in which uncertainty around policy announcements delays belief formation and depresses confidence.

Figures 7c and 7d show that CPU shocks also affect real economic outcomes, as private non-residential investment declines by approximately 0.24% at its peak, while industrial production falls by 0.55%. Both responses are statistically significant and condensed within the first months after the shock.

These patterns are consistent with the theoretical prediction that uncertainty delays or depresses capital-intensive investments, particularly when the credibility of long-term policy signals is unclear. The reduction in industrial production reflects broader real economy spillovers from weakened sentiment and lower investment. Together, these results indicate that CPU operates as a supply-side drag, increasing transition costs and slowing the pace of economic adjustment.

Finally, Figure 7e reports the estimated response of the Dutch AEX stock index. Stock prices decline significantly, with a peak cumulative reduction of 2.16% within six months. This reaction suggests that financial markets internalize the implications of CPU for firm earnings, regulatory risk, and transition costs. Rising CPU-Concern leads to an increase in perceived downside risk, prompting a repricing of equity valuations and higher risk premia.[2]

[2] Section C of the Appendix provides a range of robustness checks, such as replacing CPU with an indicator of total uncertainty (Figure A.4), including Economic Sentiment and Industrial Confidence alternatively in the model (Figures A.6 and A.7), accounting for the Covid-19 period (Figure A.5).

Overall, these results confirm that CPU has measurable short-term effects on economic expectations, real activity, and financial markets. The findings are consistent with the conceptual framework outlined in Section 3 and with theoretical insights from the broader literature on policy uncertainty and credibility. Unexpected increases in CPU depress economic sentiment and confidence, reduce investment and production, and trigger a decline in stock market valuations. These channels suggest that policy-induced uncertainty can act as a short-term drag on economic performance during the low-carbon transition.

6.3 Isolating the expectations channel

To better gauge the relevance of the expectations channel in amplifying the impact of CPU, in this section we run counterfactual simulations whereby we shut down the response of Economic Sentiment and Industrial Confidence to a CPU shock for 12 months.[3] We then assess the IRFs of the other variables of interest against our baseline results (Figure 8).

Results show that the impact of CPU shocks is muted compared to the baseline. While we still find some negative effects on both industrial production (Figure 8b) and stock market valuations (Figure 8c), the magnitude is, respectively, around 60% and 30% smaller at the peak compared to the baseline results.[4]

These findings underscore the critical role of expectations in the transmission of uncertainty shocks. The macroeconomic literature has long emphasized that economic agents form expectations about future conditions, including policies, regulations, and risks, and that these expectations directly influence current behavior (Bloom, 2009, Bachmann and Sims, 2012 and Leduc and Liu, 2016). In the case of climate policy, uncertainty can distort firms' expectations about the regulatory and investment environment, leading to precautionary reductions in investment and hiring. Similarly, households may revise their consumption and savings decisions in anticipation of possible shifts in energy costs or labor market implications.

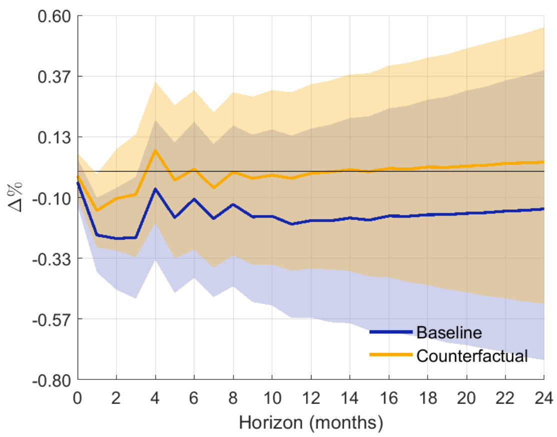
The substantial attenuation of the IRFs under the counterfactual scenario suggests that a significant portion of the impact of CPU shocks operates through forward-looking channels.

[3]Refer to Section B of the Appendix for details on the counterfactual simulations.

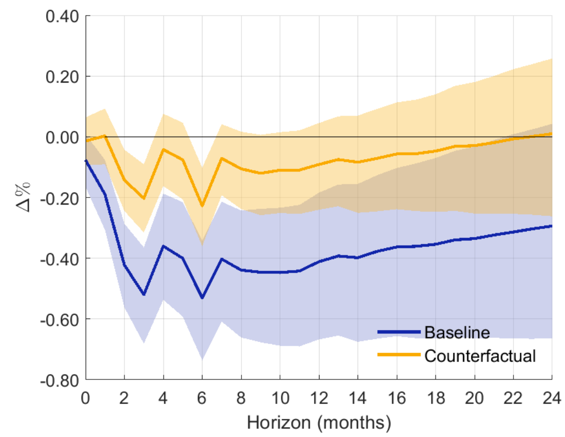
[4]However, such difference is statistically significant only in the case of industrial production. Refer to Figure A.3 in the Appendix for a decomposition of the difference between baseline and counterfactual IRFs that teases out ES and IC contributions.

Figure 8: Impact of climate policy uncertainty shocks–baseline vs counterfactual

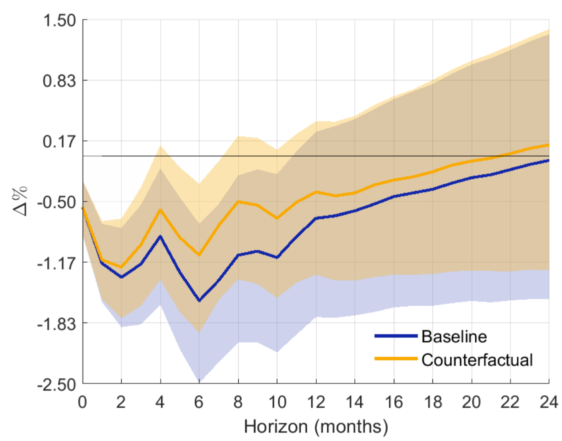
(a) Investment



(b) Industrial Production



(c) Stock Market Index



Note: Impulse response functions (IRFs) to a one-standard-deviation shock to climate policy uncertainty. In the counterfactual simulations (yellow line), we shut down the response of Economic Sentiment and Industrial Confidence. Shaded areas represent 68% highest posterior density intervals. Variables are expressed in percentage change relative to baseline.

This is consistent with models incorporating news shocks or anticipated policy changes, where even shocks with no immediate real effects can influence macroeconomic dynamics by altering beliefs (e.g., Beaudry and Portier, 2006). Our findings also align with more recent evidence whereby business confidence and sentiment indicators often act as catalysts of uncertainty effects, amplifying real responses before fundamental shocks fully materialize (Barsky and Sims, 2012 and Altig et al., 2019).

Relatedly, Gambetti et al. (2023) show that only agreed uncertainty, where expectations are broadly aligned, generates strong macroeconomic effects, further reinforcing the importance of sentiment coordination in shaping real outcomes. The results imply that policy uncertainty affects the economy not merely through informational noise, but through its impact on collective beliefs about policy credibility. Therefore, ignoring the expectations channel would lead to a significant underestimation of the macroeconomic consequences of climate policy uncertainty. Our results highlight the need for policymakers to manage not only the substance of climate policy, but also its predictability and clarity in order to avoid unintended adverse effects via expectations.

6.4 Negative vs positive shocks

This section investigates the asymmetric macroeconomic effects of positive and negative CPU-Concern shocks, by looking at how real and financial indicators respond differently depending on the direction of the shock. Understanding this asymmetry is indeed essential for evaluating the full transmission mechanism of uncertainty shocks and for designing effective policy communication strategies during the climate transition. In order to do so, we construct two separate CPU indexes as follows:

$$\text{CPU-Concern}_t^+ = \frac{N_t^+}{TN_t^+}, \quad \text{where } N_t^+ = \#\{n : \text{Sentiment}_{n,t} < 0.5\}$$
$$\text{CPU-Concern}_t^- = \frac{N_t^-}{TN_t^-}, \quad \text{where } N_t^- = \#\{n : \text{Sentiment}_{n,t} > 0.5\}$$

In other words, we construct two Baker-type indicators, capturing the media attention to climate policy uncertainty – in the climate policy domain – considering only articles whose sentiment is either positive or negative, according to Equation (1).

Figure 9 depicts the IRFs to positive and negative CPU shocks. All the variables of interest seem to react more strongly and persistently to negative CPU shocks (red lines) compared to positive shocks (green lines). This asymmetry is particularly pronounced for forward-looking variables like Economic Sentiment and Industrial Confidence (Figures 9a and 9b) and stock market valuations (Figure 9e).

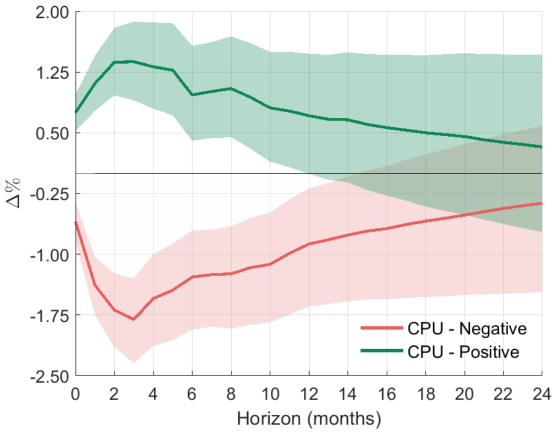
Negative CPU shocks, indeed, trigger a sharp and persistent decline in Economic Sentiment and Industrial Confidence, with troughs occurring around 4–6 months after the shock and values remaining below baseline over the 12-month horizon. By contrast, positive CPU shocks result in smaller and more short-lived improvements in confidence indicators. This suggests that while favorable news about climate policy may temporarily boost expectations, the harmful effects of increasing uncertainty, likely driven by precautionary behavior and heightened risk aversion, are more influential and durable.

These divergent confidence responses are mirrored in real and financial outcomes. Investment and industrial production drop markedly following negative CPU shocks, consistent with firms postponing capital expenditures in the face of uncertain regulatory conditions. As to the stock market prices, positive CPU shocks generate sustained gains of up to 2% after four months, while negative shocks induce a swift and sizable contraction in the shorter-run (up to two months). This seems to reflect a rapid repricing of perceived risk and future earnings expectations.

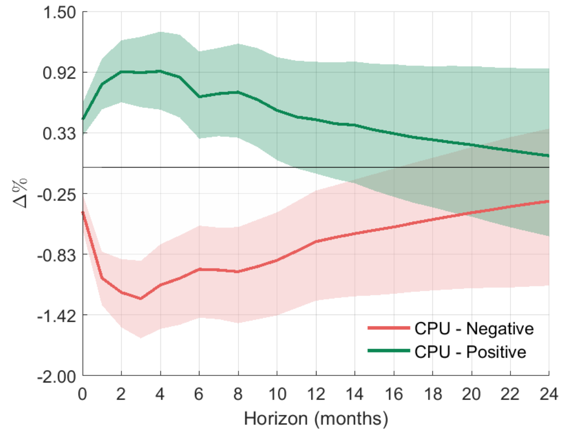
Our findings are consistent with the growing literature on the nonlinear effects of uncertainty, with contractions following negative shocks being much stronger than the expansions from positive ones (Bloom, 2009; Caggiano et al., 2017; Fernández-Villaverde et al., 2022; Lenoël and Young, 2021). In the specific context of climate policy, Ilzetzki et al. (2023) highlight how ambiguous or abrupt announcements increase macroeconomic volatility and dampen private sector responses, even when the policy direction is aligned with long-run goals. From a theoretical standpoint, Kozlowski et al. (2020) show that rare and ambiguous events can permanently shift belief distributions, reinforcing pessimism. Moreover, models of informational rigidities (Vavra, 2014) suggest that increased uncertainty inflates the perceived variance of future states, which in turn amplifies the economic agents' precautionary responses. Bachmann et al. (2022), instead, emphasize how narrative expectations, shaped

Figure 9: Impact of climate policy uncertainty shocks–positive vs negative shocks

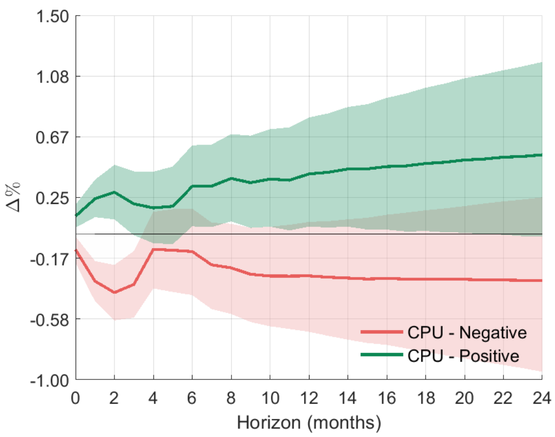
(a) Economic Sentiment



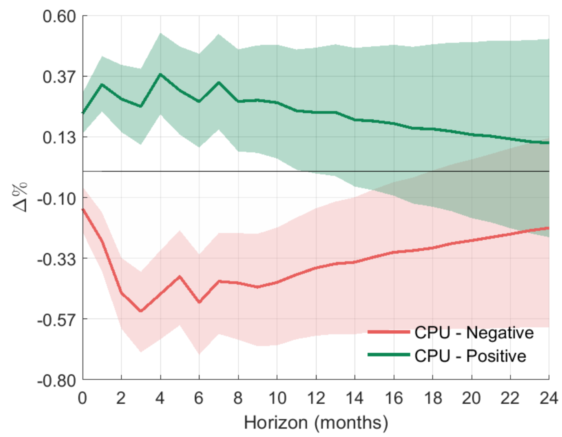
(b) Industrial Confidence



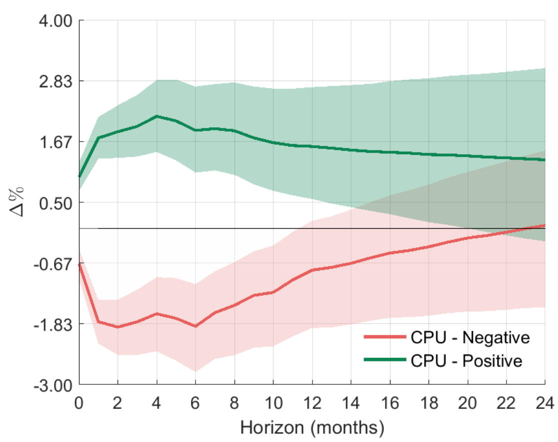
(c) Investment



(d) Industrial Production



(e) Stock Market Index



Note: Impulse response functions (IRFs) to one-standard-deviation positive (green) and negative (red) shocks to climate policy uncertainty. Shaded areas represent 68% highest posterior density intervals. Variables are expressed in percentage change relative to baseline.

by media, policy signals, or prevailing sentiment, can amplify the real effects of uncertainty via belief-driven fluctuations. More recently, Gambetti et al. (2023) have provided evidence of different impact of uncertainty depending on disagreement.

In the context of climate policy, where regulatory change may entail significant structural transformations and compliance costs, negative CPU shocks likely heighten perceptions of downside risk. The asymmetric responses observed here highlight the importance of predictable and transparent policy frameworks in mitigating the adverse macroeconomic consequences of climate-related uncertainty.

6.5 Impact on prices

From the results discussed above, we infer that CPU can have relevant macroeconomic effects in the short-run. In this section, we want to investigate the nature of such impacts, i.e., whether they are more supply or demand-driven. With this aim, we include the consumers' price level, as quantified by the HICP, among the endogenous variables in Equation (3), and we order it after industrial production.[5] We then apply the same recursive identification scheme as explained in Section 6.1.

Figure 10 depicts the IRFs of HICP to a one-standard-deviation shock in the CPU-Concern Index in the baseline framework (Figure 10a), when disentangling between positive and negative shocks (Figure 10b) and when shutting down the expectations channel (Figure 10c). All in all, a CPU shock entails a short-lived increase in prices by up to +0.14% three months after the shock. However, the rise becomes much more relevant and persistent after a positive shock (+0.33% over the 24-month horizon), the opposite of what observed for the other variables. Taken together with the results for investment and industrial production, this finding suggests that negative CPU shocks configure more as negative supply shocks, characterized by a contraction in economic activity and a temporary increase in prices, whereas positive CPU shocks are more similar to positive demand shocks, featuring an expansion in output accompanied by a longer-lasting rise in prices. Our findings, then, also contribute to the growing literature on uncertainty and monetary policy. In contrast to

[5]This ordering is based on the assumption, widely made by the relevant literature, that shocks first propagate through the economy before affecting the price level, which derives from the causal structure implied by New Keynesian models (see Stock and Watson, 2005; Bianchi et al., 2023).

studies that treat uncertainty shocks as uniformly contractionary (e.g.,Bloom, 2009; Leduc and Liu, 2016), our results align more with recent work by Carceller del Arco and van den End (2023), who argue that monetary policy should respond cautiously to supply-driven, but more actively to demand-driven uncertainty. This would potentially call for a state-contingent policy approach, whereby central banks should not uniformly "look through" CPU shocks, but, instead, tailor their response based on the underlying nature of the shock. In our specific case, negative CPU shocks resemble adverse supply shocks, characterized by falling investment and industrial production and temporarily rising prices. In this context, the *Brainard principle* (Brainard, 1967) would advocate for a measured response to such shocks, as too an aggressive tightening could aggravate the contraction. Conversely, positive CPU shocks exhibit demand-like features, with output and prices increasing together, the latter more persistently. In this context, the central bank may need to respond more actively.

Finally, as already observed for the other variables, the change in prices becomes insignificant when shutting down the reaction of Economic Sentiment and Industrial Confidence, which underscores once more the importance of the expectations channel in the transmission of uncertainty shocks to the economy.

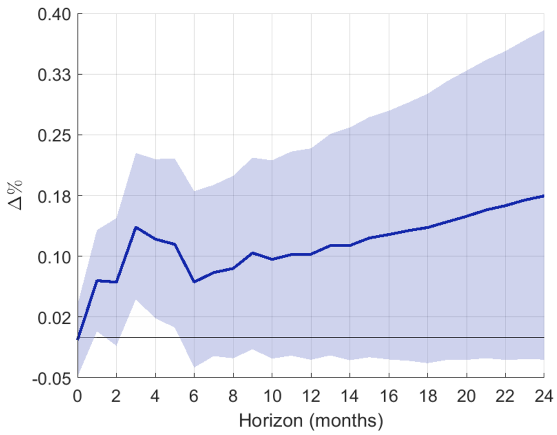
7 Policy Implications

The results presented in this paper have clear implications for the design and communication of climate policy. Our analysis demonstrates that CPU, and the concern associated with it, is not merely a byproduct of public debate but an economically meaningful phenomenon with measurable effects on expectations, investment behavior, and financial markets. CPU acts as a source of macroeconomic volatility, reducing business confidence and delaying capital formation in the short term.

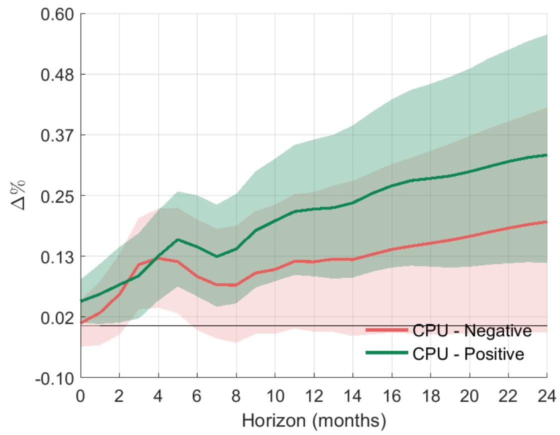
A first implication concerns the importance of policy credibility. The evidence shows that uncertainty is endogenous to the legislative process and political communication. CPU spikes during early stages of policymaking, when the content, timing, and enforcement of climate measures remain unclear, and declines only after formal ratification. This dynamic mirrors insights from the broader literature on monetary and fiscal policy credibility (Bernanke et al.,

Figure 10: Impact of climate policy uncertainty shocks on HICP

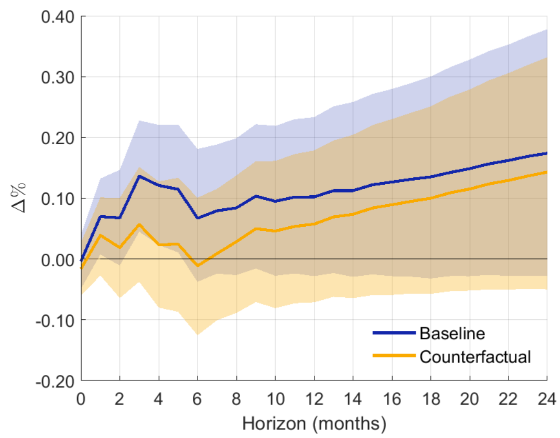
(a) Baseline



(b) Positive vs negative shocks



(c) Counterfactual



Note: Impulse response functions (IRFs) to a one-standard-deviation shock to climate policy uncertainty. In the counterfactual simulations (yellow line), we shut down the response of Economic Sentiment and Industrial Confidence. Shaded areas represent 68% highest posterior density intervals. HICP is expressed in percentage change relative to baseline.

2004; Faust and Svensson, 2001): stable, predictable, and credible policy frameworks reduce informational frictions and mitigate precautionary behavior by firms and investors.

Second, the empirical results suggest that the structure and communication of climate policy shape its economic consequences. Our analysis highlights heterogeneity across policy types. Policies with visible distributional consequences or cost implications, such as carbon pricing, generate more persistent uncertainty, even when legislative timelines are short. Framework laws and long-term targets, by contrast, produce uncertainty primarily during early announcement phases. This heterogeneity implies that governments can reduce the economic costs of CPU by minimizing ambiguity in policy design, providing early clarity on implementation mechanisms, and credibly committing to long-term targets.

Third, the findings emphasize that some degree of policy uncertainty is inevitable and, in some cases, even desirable. Climate policy must retain flexibility to respond to evolving technologies, preferences, and external shocks. The objective is therefore not to eliminate uncertainty entirely but to strike an optimal balance between flexibility and credibility. Excessive rigidity may hinder adaptive policy responses, while persistent ambiguity increases transition costs and delays investment.

From a normative perspective, our results seem to suggest that CPU generates real economic costs through delays in capital formation, reduced production, and higher risk premia in financial markets. These costs may compound over time, slowing the transition to a low-carbon economy. In welfare terms, CPU can be conceptualized as an informational friction that reduces the efficiency of resource allocation during the climate transition.

Policy design can mitigate these costs through institutional mechanisms that enhance commitment and transparency. Long-term policy frameworks, such as climate laws anchored in legislation, reduce uncertainty by establishing credible pathways. Complementary instruments, including forward guidance, stable subsidy schemes, and regulatory clarity, can further anchor expectations. Conversely, frequent policy reversals, ambiguous communication, and protracted legislative processes amplify CPU and its economic effects.

More broadly, these findings underscore the need to incorporate policy-induced uncertainty into the economic assessment of climate transition pathways. Standard cost-benefit analyses typically overlook the macroeconomic costs of CPU. By integrating uncertainty dynamics into policy evaluation, governments can better account for the transition costs associated with credibility gaps and informational frictions.

Our analysis also encompasses an evaluation of the effects of CPU for prices as well as the potential implications for monetary policy. In light of our findings, the central bank might be induced to change its stance, depending on the nature of the CPU shock.

Finally, our results point to avenues for future research. While the analysis focuses on short-term macroeconomic effects, the long-term consequences of CPU – especially its impact on green investment, innovation, and structural economic transformation – remain underexplored. Understanding how policy credibility affects the cost of capital, risk premia, and firm-level investment decisions is critical for designing efficient climate policy in a context of uncertainty.

8 Conclusion

This paper provides new evidence on the economic relevance of climate policy uncertainty (CPU) and its role in shaping macroeconomic outcomes. It makes four distinct contributions.

First, we develop a novel, media-based index of CPU for the Netherlands. Unlike existing indices, our measure accounts not only for the prevalence of uncertainty in climate policy debates but also for the sentiment and tone of media coverage. The index is normalized relative to the volume of climate policy news, enabling consistent comparison across time and with broader policy uncertainty measures.

Second, we document how CPU evolves over the legislative cycle. Drawing from insights in the fiscal and monetary policy literature, we show that CPU follows a predictable pattern: it rises during the early stages of policy formulation, reflecting public debate and political contention, and declines upon formal ratification and publication. This dynamic highlights the informational role of institutional processes and policy communication in shaping perceived uncertainty.

Third, we provide empirical evidence on the economic effects of CPU shocks. Building on a conceptual framework that emphasizes policy credibility and commitment, we estimate a monthly BVAR model to trace the short-term macroeconomic impact of CPU shocks. We find that rising CPU significantly reduces business confidence, investment sentiment, and financial market performance. These effects are primarily driven by expectations: counterfactual simulations show that shutting down the response of economic sentiment and industrial confidence substantially attenuates the impact on real activity. This provides one of the first direct tests of the expectations channel in the context of climate policy, and underscores how uncertainty operates through coordinated belief formation.

Fourth, we find that the macroeconomic consequences of CPU are asymmetric. Negative CPU shocks, those reflecting rising concern, pessimistic tone, or doubts about implementation, generate significantly larger and more persistent economic impacts than positive shocks. This asymmetry suggests that the economic costs of CPU are not just a function of its frequency, but of how uncertainty is framed and perceived. It also reinforces the idea that downside risks in public expectations matter more than mere policy volatility.

Fifth, we present evidence of the differential impact of CPU shocks on prices. A negative CPU shock is more akin to a negative *supply* shock, whereas a positive CPU shock is more akin to a positive *demand* shock. This, in turn, may have significant implications for monetary policy.

Taken together, these findings show that CPU can meaningfully influence short-run macroeconomic conditions by undermining confidence and delaying investment. They also reveal that the credibility and clarity of climate commitments are central to minimizing these effects. Climate policy uncertainty is not just a byproduct of institutional complexity, it is a measurable and consequential economic force.

Our results highlight the importance of credible, transparent, and stable climate policy frameworks for supporting the low-carbon transition. Future research should examine the long-term consequences of CPU, including its effects on financing conditions, green technology adoption, innovation incentives, and structural transformation. As climate policy becomes increasingly central to economic planning, understanding and managing its uncertainty will be critical to sustaining both macroeconomic stability and environmental ambition.

References

[1] Altig, D., Baker, S., Barrero, J. M., Bloom, N., Bunn, P., Chen, S., et al. "Measuring the effect of uncertainty on investment". *Brookings Papers on Economic Activity*, 2019 (2):249–330, 2019.

[2] Ardia, D., Bluteau, K., Boudt, K., and Inghelbrecht, K. "Climate change concerns and the performance of green vs. brown stocks". *Management Science*, 69(12):7607–7632, 2023.

[3] Bachmann, R. and Sims, E. R. "Uncertainty and economic activity: Evidence from business survey data". *American Economic Journal: Macroeconomics*, 4(2):217–249, 2012.

[4] Bachmann, R., Carstensen, K., and Lautenbacher, S. "Narrative expectations and macroeconomic fluctuations". *American Economic Journal: Macroeconomics*, 14(3): 185–215, 2022.

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

[6] Barsky, R. B. and Sims, E. R. "Information, animal spirits, and the meaning of innovations in consumer confidence". *American Economic Review*, 102(4):1343–1377, 2012.

[7] Basaglia, P., Berestycki, C., Carattini, S., Dechezleprêtre, A., and Kruse, T. "Climate policy uncertainty and firms' and investors' behavior". Technical report, CESifo Working Paper, 2025.

[8] Battiston, S., Monasterolo, I., Riahi, K., and van Ruijven, B. "Accounting for finance is key for climate mitigation pathways". *Science*, 372:918–920, 2021.

[9] Beaudry, P. and Portier, F. "Stock prices, news, and economic fluctuations". *American Economic Review*, 96(4):1293–1307, 2006.

[10] Berestycki, C., Carattini, S., Dechezleprêtre, A., and Kruse, T. "Measuring and assessing the effects of climate policy uncertainty". OECD Working Paper, 2022.

[11] Bernanke, B., Reinhart, V., and Sack, B. "Monetary policy alternatives at the zero bound: An empirical assessment". *Brookings papers on economic activity*, 2004(2):1–100, 2004.

[12] Bernanke, B. S., Gertler, M., and Watson, M. "Systematic monetary policy and the effects of oil price shocks". *Brookings Papers on Economic Activity*, 1997(1):91–157, 1997.

[13] Bianchi, F., Nicolò, G., and Song, D. "Inflation and real activity over the business cycle". NBER Working Papers 31075, National Bureau of Economic Research, Inc, Mar 2023.

[14] Bloom, N. "The impact of uncertainty shocks". *Econometrica*, 77(3):623–685, 2009.

[15] Brainard, W. C. "Uncertainty and the effectiveness of policy". *The American Economic Review*, 57(2):411–425, 1967.

[16] Caggiano, G., Castelnuovo, E., and Figueres, J. "Economic policy uncertainty spillovers in the euro area". *Economics Letters*, 158:85–90, 2017.

[17] Campiglio, E. and van der Ploeg, F. "Macrofinancial risks of the transition to a low-carbon economy". *Review of Environmental Economics and Policy*, 16(2):173–195, 2002.

[18] Campiglio, E., Lamperti, F., and Terranova, R. "Believe me when I say green! Heterogeneous expectations and climate policy uncertainty". *Journal of Economic Dynamics and Control*, 165:1–31, 2024.

[19] Carceller del Arco, M. and van den End, J. W. "Robust monetary policy under shock uncertainty". Working Papers 793, DNB, Oct 2023.

[20] Faust, J. and Svensson, L. E. "Transparency and credibility: Monetary policy with unobservable goals". *International Economic Review*, 42(2):369–397, 2001.

[21] Fernández-Villaverde, J., Guerrón-Quintana, P., Kuester, K., and Rubio-Ramírez, J. F. "Uncertainty shocks and business cycle research". *Journal of Economic Literature*, 60 (2):345–392, 2022.

[22] Forni, M., Gambetti, L., and Sala, L. "Downside and upside uncertainty shocks". *Journal of the European Economic Association*, 23(1):159–189, 2025.

[23] Fried, S., Novan, K., and Peterman, W. B. "Climate policy transition risk and the macroeconomy". *European Economic Review*, 147(104174):1–23, 2022.

[24] Frondel, M., Simora, M., and Sommer, S. "Risk perception of climate change: Empirical evidence for germany". *Ecological Economics*, 137:173–183, 2017.

[25] Fuss, S., Szolgayova, J., Obersteiner, M., and Gusti, M. "Investment under market and climate policy uncertainty". *Applied Energy*, 85(8):708–721, 2008.

[26] Gambetti, L., Korobilis, D., Tsoukalas, J. D., and Zanetti, F. "Agreed and Disagreed Uncertainty". Discussion Papers 2304, Centre for Macroeconomics (CFM), Feb. 2023.

[27] Gavriilidis, K. "Measuring climate policy uncertainty". Technical report, 2021.

[28] Helm, D., Hepburn, C., and Mash, R. "Credible carbon policy". *Oxford Review of Economic Policy*, 19(3):438–450, 2003.

[29] Houari, O., Bennani, H., and Bro de Comères, Q. "Climate risks and economic activity in france: Evidence from media coverage". *Journal of International Money and Finance*, 155:103340, 2025.

[30] Ilzetzki, E., Jain, S., and Fatás, A. "How important are policy announcements for macroeconomic volatility? Evidence from U.S. climate policy". *NBER Working Paper No. 31691*, 2023. Forthcoming, Review of Economics and Statistics.

[31] Kozlowski, J. K., Veldkamp, L., and Venkateswaran, V. "Longer-run economic consequences of pandemics". *Journal of Political Economy*, 128(11):3838–3875, 2020.

[32] Leduc, S. and Liu, Z. "Uncertainty shocks are aggregate demand shocks". *Journal of Monetary Economics*, 82:20–35, 2016.

[33] Leduc, S. and Liu, Z. "Uncertainty shocks are aggregate demand shocks". *Journal of Monetary Economics*, 82:20–35, 2016. ISSN 0304-3932.

[34] Lemoine, D. "Green expectations: current effects of anticipated carbon pricing". *Review of Economics and Statistics*, 99(3):499–513, 2017.

[35] Lenoël, C. and Young, G. "Uncertainty shocks, capital flows, and the international transmission of business cycles". *IMF Economic Review*, 69(1):66–108, 2021.

[36] Lenza, M. and Primiceri, G. E. "How to estimate a VAR after March 2020". *Journal of Applied Econometrics*, 37(4):688–699, 2022.

[37] Loughran, T. and McDonald, B. "When is a liability not a liability? Textual analysis, dictionaries, and 10ks". *Journal of Finance*, 66(1):35–65, 2011.

[38] Melosi, L., Morita, H., Rogantini Picco, A., and Zanetti, F. "The signaling effects of fiscal announcements". CESifo Working Paper, 2024.

[39] Mumtaz, H. and Theodoridis, K. "Monetary policy and macroeconomic uncertainty: Evidence from the euro area". *Journal of Monetary Economics*, 114:237–255, 2020.

[40] Nemet, G. F., Jakob, M., Steckel, J. C., and Edenhofer, O. "Addressing policy credibility problems for low-carbon investment". *Global Environmental Change*, 42:47–57, 2017.

[41] Noailly, J., Nowzohour, L., Van Den Heuvel, M., and Pla, I. "Heard the news? environmental policy and clean investments". *Journal of Public Economics*, 238:105190, 2024.

[42] PBL Netherlands Environmental Assessment Agency. "Climate and energy outlook of the Netherlands 2024", 2024. URL https://www.pbl.nl/en/publications/climate-and-energy-outlook-of-the-netherlands-2024.

[43] Sims, C. A. "Interpreting the macroeconomic time series facts: The effects of monetary policy". *European Economic Review*, 36(5):975–1011, 1992.

[44] Sims, C. A. "Computational methods for the study of dynamic economies". *Handbook of Computational Economics*, 1:1171–1230, 1995.

[45] Stock, J. H. and Watson, M. W. "Implications of dynamic factor models for var analysis". NBER Working Papers 11467, National Bureau of Economic Research, Inc, Jul 2005.

[46] van der Ploeg, F. "Climate policy: challenges and obstacles". In Cnossen, S. and Jacobs, B., editors, *Tax by Design for the Netherlands*, pages 329–341. Oxford University Press, 2021.

[47] Van Der Straten, Y., Perotti, E., and van der Ploeg, F. "Political economy of climate change adaptation". Tinbergen Institute Discussion Paper, 2024.

[48] Vavra, J. "Inflation dynamics and time-varying volatility: New evidence and an ss interpretation". *The Quarterly Journal of Economics*, 129(1):215–258, 2014.

[49] Vona, F., Marin, G., Consoli, D., and Popp, D. "Environmental regulation and green

skills: an empirical exploration". *Journal of the Association of Environmental and Resource Economists*, 5:713–753, 2018.

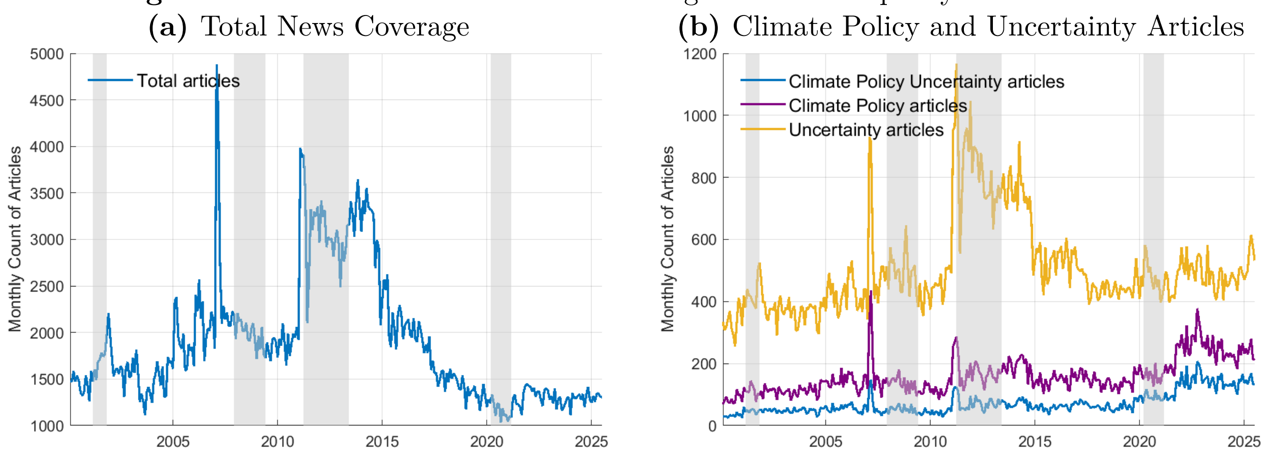
Appendix

A Additional Tables and Figures

Table A.1: English translation of Dutch keywords used in constructing the CPU index, grouped into climate-related terms, policy-related terms and uncertainty terms.

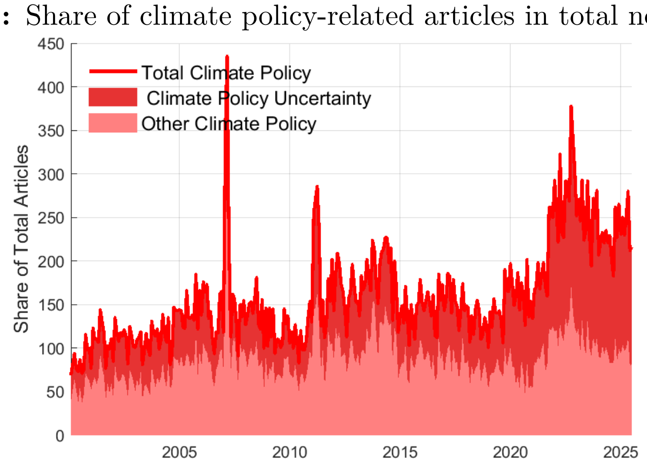
Climate words			Policy terms	Uncertainty terms
Paris agreement	ETS	kyoto protocol	tax	risk
biobased	fine dust	methane	policy	uncertain
biofuel	green deal	environment	cabinet	doubtful
biodiesel	renewable	nuclear	government	hesitation
biodiversity	IPCC	warming	measure	tension
biogas	nuclear energy	coal	regulation	unrest
organic	road pricing	nitrogen	standardization	threat
biomass	climate agreements	urgenda	government	concern about
bioplastic	climate accord	water quality	law	unpredictable
biotech	climate ambitions	flooding	legislation	fear
fuel	climate conference	water level	climate treaty	
greenhouse gas	climate crisis	hydrogen		
lignite	climate goal	wind		
certificate	climate fund	sea level rise		
CO2	climate measure	solar boilers		
sustainable	climate minister	solar cell		
electric biking	climate neutral	solar collectors		
electric driving	climate panel	solar roof		
electric car	climate plan	solar panel		
low-emission	climate problem	solar park		
emissions trading	climate risk	solar power		
emission price	climate summit	sulfur		
emission right	climate change	climate science		
emission reduction	carbon dioxide			
energy	carbon			

Figure A.1: Evolution of total news coverage and climate policy-related articles



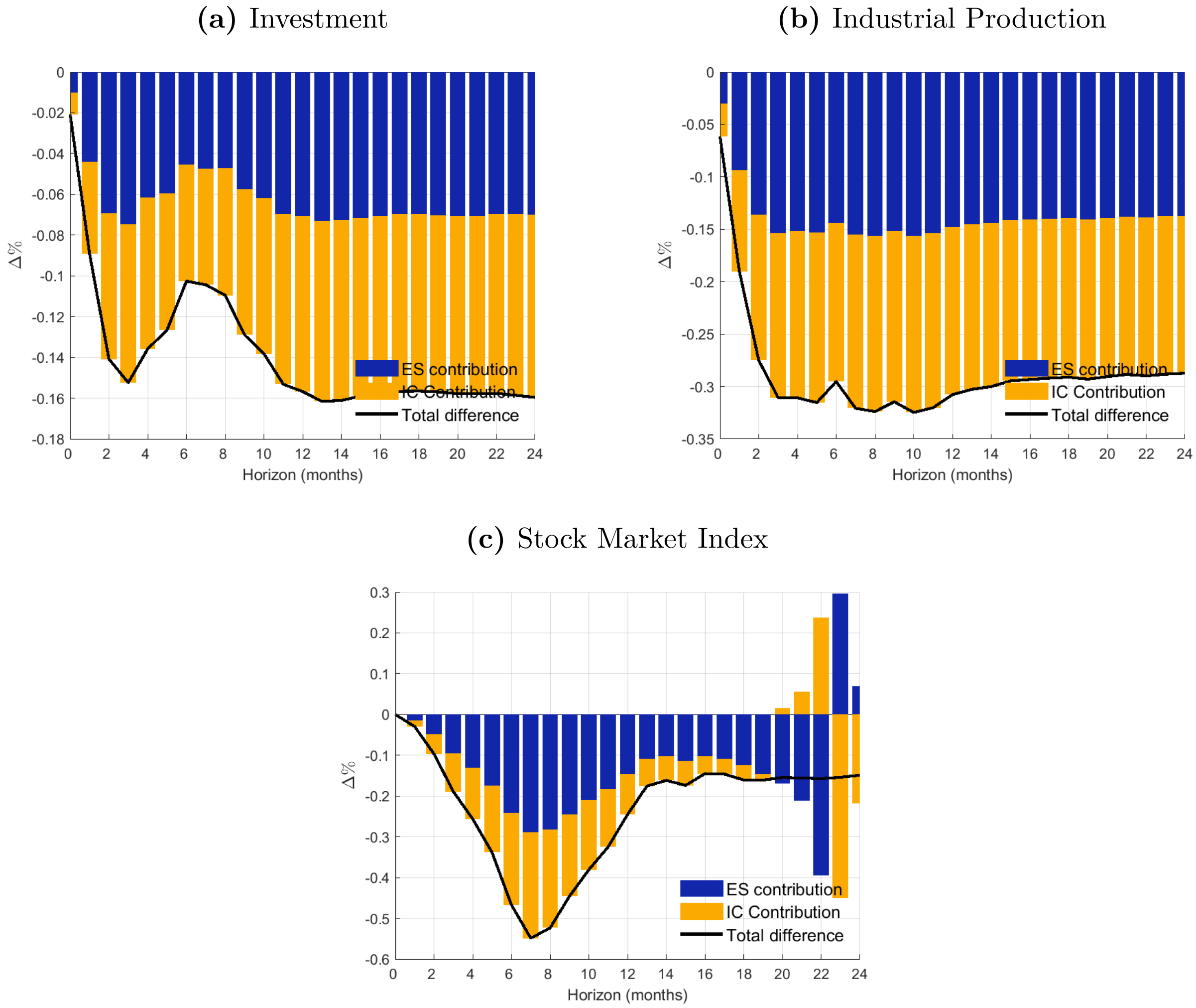
Note: The left panel shows the monthly count of total newspaper articles published in the Netherlands from 2000 to 2025. The right panel reports the monthly count of articles mentioning climate policy uncertainty, climate policy, and uncertainty more broadly. Shaded areas indicate periods of major economic or political uncertainty.

Figure A.2: Share of climate policy-related articles in total news coverage



Note: The figure shows the monthly share of climate policy articles in total news coverage from 2000 to 2025, decomposed into articles related to climate policy uncertainty and other climate policy topics.

Figure A.3: Decomposition of difference between baseline and counterfactual IRFs



Note: Median difference in the impulse response functions (IRFs) to a one-standard-deviation shock to climate policy uncertainty. In the counterfactual simulations, we shut down the response of Economic Sentiment and Industrial Confidence.

B Counterfactual Analysis

This section explains the counterfactual analysis performed in Section 6 above, which draws from Sims (1992, 1995) and Bernanke et al. (1997), and aligns with the methodology used in recent empirical macroeconomic studies such as Mumtaz and Theodoridis (2020).

We consider the reduced-form *monthly* BVAR:

$$\boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{A_i} \boldsymbol{y}_{t-i} + \boldsymbol{u}_t, \quad \boldsymbol{u}_t \sim \mathcal{N}(0, \Sigma_u)$$

and its structural form:

$$\boldsymbol{A_0} \boldsymbol{y}_t = \sum_{i=1}^{p} \boldsymbol{C_i} \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}(0, \boldsymbol{I_n})$$

with $\boldsymbol{A_0}^{-1} \boldsymbol{\varepsilon}_t = \boldsymbol{u}_t$. As explained in Section 6 above, the matrix $\boldsymbol{A_0}$ is identified via a Cholesky decomposition of Σ_u, so that $\Sigma_u = \boldsymbol{A_0} \boldsymbol{A_0'}$. The VAR(p) can be expressed as a VAR(1) in companion form:

$$\boldsymbol{Z}_t = \mathcal{B} \boldsymbol{Z}_{t-1} + \boldsymbol{v}_t,$$

with

$$\boldsymbol{Z}_t = \begin{bmatrix} \boldsymbol{y}_t \\ \boldsymbol{y}_{t-1} \\ \vdots \\ \boldsymbol{y}_{t-p+1} \end{bmatrix} \in \mathbb{R}^{np},$$

$$\mathcal{B} = \begin{bmatrix} \boldsymbol{A_1} & \boldsymbol{A_2} & \cdots & \boldsymbol{A_{p-1}} & \boldsymbol{A_p} \\ I_n & 0 & \cdots & 0 & 0 \\ 0 & I_n & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \boldsymbol{I_n} & 0 \end{bmatrix},$$

and

$$\boldsymbol{v}_t = \begin{bmatrix} \boldsymbol{u}_t \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

Iterating backward, we obtain the moving average representation:

$$\boldsymbol{Z}_t = \sum_{h=0}^{\infty} \mathcal{B}^h \boldsymbol{v}_{t-h}.$$

To extract the impulse response function for $\boldsymbol{y_t}$, define the selection matrix:

$$J = \begin{bmatrix} \boldsymbol{I_n} & 0 & \cdots & 0 \end{bmatrix} \in \mathbb{R}^{n \times np}.$$

Then, the impulse response function at horizon h is given by:

$$\Phi_h = J \mathcal{B}^h J',$$

so that:

$$\boldsymbol{y}_t = \sum_{h=0}^{\infty} \Phi_h \boldsymbol{u}_{t-h}.$$

Orthogonal impulse responses can be obtained using the Cholesky decomposition of $\boldsymbol{\Sigma_u}$, yielding:

$$\Psi_h = \Phi_h \boldsymbol{A_0}.$$

The impulse response at horizon h is hence given by:

$$\boldsymbol{y}_{t+h} = \Psi_h \boldsymbol{\varepsilon}_t$$

We aim to isolate the impact of a structural shock – in our case the CPU-Concern – while setting the response of other $n = 2$ variables — Economic Sentiment (ES) and Industrial

Confidence (IC) – to zero over $K = 12$ months. We hence construct a $K \times 3$ shock vector:

$$\boldsymbol{\varepsilon}^{\text{cf}} = \begin{bmatrix} \underbrace{\varepsilon_{CPU}}_{K\times 1} & \underbrace{\boldsymbol{\eta}}_{K\times 2} \end{bmatrix},$$

where ε_{CPU} is the primary CPU shock and $\boldsymbol{\eta}$ includes K auxiliary shocks for ES and IC. We define the objective function as:

$$f(\boldsymbol{\varepsilon}^{\text{cf}}) = \begin{bmatrix} \Psi_0^{(ES,IC)}\boldsymbol{\varepsilon}^{\text{cf}} - \text{target}^0_{ES,IC} \\ \text{vec}(\Psi_1^{(ES,IC)}\boldsymbol{\varepsilon}^{\text{cf}} - \text{target}^{(1)}_{ES,IC}) \\ \vdots \\ \text{vec}(\Psi_K^{(ES,IC)}\boldsymbol{\varepsilon}^{\text{cf}} - \text{target}^{(K)}_{ES,IC}) \end{bmatrix},$$

where *target* is a vector specifying the desired IRFs, e.g. zeros for ES and IC. We then solve $\min_{\boldsymbol{\varepsilon}^{\text{cf}}} \|f(\boldsymbol{\varepsilon}^{\text{cf}})\|^2$ to retrieve the vector of simulated shocks for ES and IC ($\boldsymbol{\eta}$). Finally, we compute the counterfactual IRFs to a unitary shock to CPU-Concern using these simulated shocks. Our procedure is conceptually similar to the counterfactual path generation in Bernanke et al. (1997), where shocks are selected to achieve a specific trajectory of endogenous variables, and to the methodology of Mumtaz and Theodoridis (2020) to estimate the propagation of shocks in VARs with stochastic volatility.

C Robustness checks

We conduct several robustness exercises to assess the stability of our results. First, we estimate the same BVAR specification using an alternative uncertainty measure based on general policy uncertainty. Specifically, we replace the climate policy uncertainty index with an index of total policy uncertainty constructed from the full set of uncertainty-related articles in *Financieele Dagblad*, without restricting to climate content. Figure A.4 reports the impulse responses to a total uncertainty shock. The estimated effects are larger in magnitude and more persistent than those of CPU-Concern shocks, particularly for investment, production, and financial markets. This finding is consistent with the broader economic literature showing that large, economy-wide uncertainty shocks produce substantial real effects. The comparison underscores that, while CPU-Concern shocks are economically relevant, their effects are smaller than those associated with broader macroeconomic uncertainty.

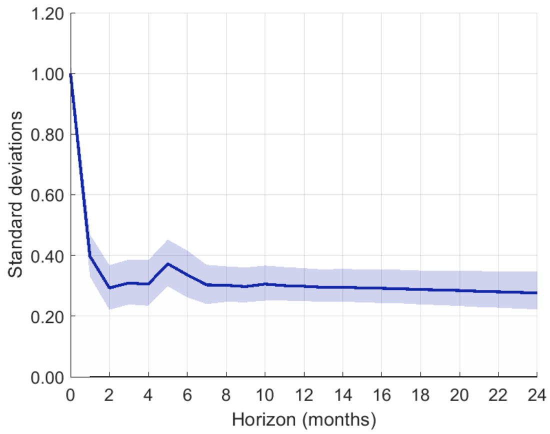
Second, we re-estimate the baseline model following the approach of Lenza and Primiceri (2022), in order to account for the Covid-19 period (see Figure A.5). This adjustment takes into consideration the temporary change in volatility induced by the pandemic and ensures that the estimated CPU-Concern shocks are not confused with pandemic-related uncertainty. Results are not qualitatively different from our baseline.

Third, we examine whether the choice of forward-looking sentiment variables affects the results. We re-estimate the BVAR model including only economic sentiment or only industrial confidence, rather than both indicators simultaneously (Figure A.6-A.7). The results remain qualitatively and quantitatively similar, confirming that the estimated effects are not sensitive to the specific choice of sentiment proxies.[6]

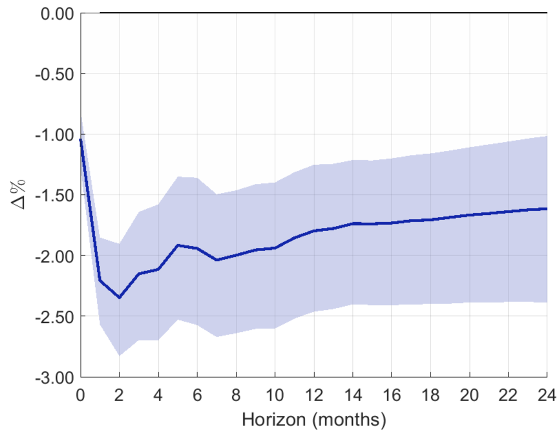
[6] In unreported exercises, we also check for the robustness of our findings to the variable ordering in the VAR and to the inclusion of energy prices (oil and gas) as exogenous controls. Results remain similar to our baseline.

Figure A.4: IRFs Total Uncertainty

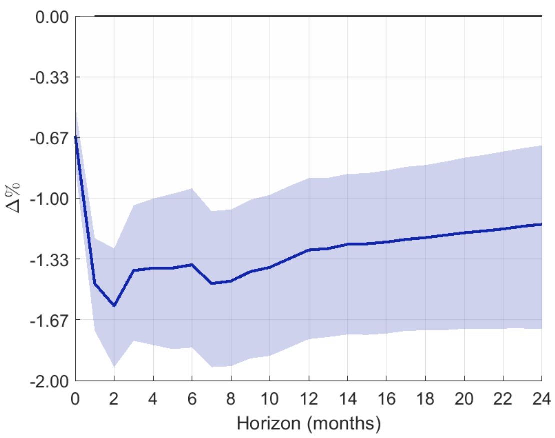
(a) Total Uncertainty



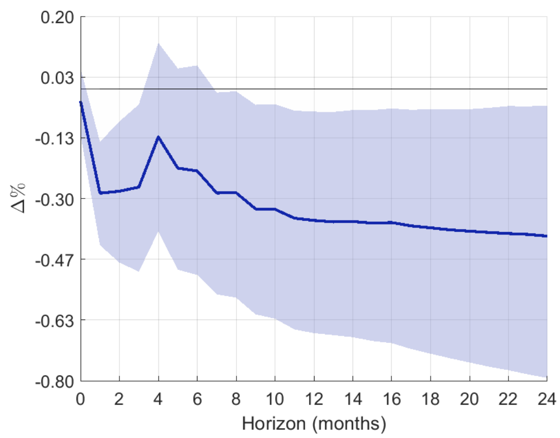
(b) Economic Sentiment



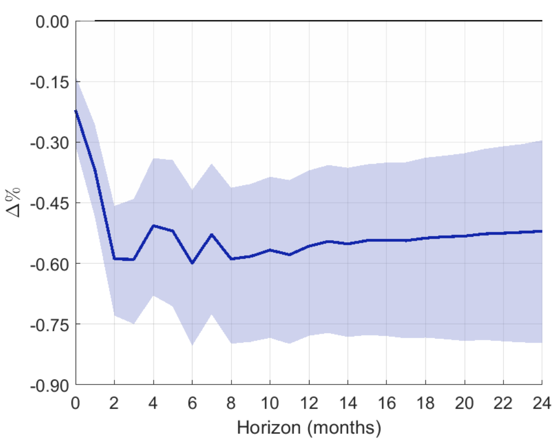
(c) Industrial Confidence



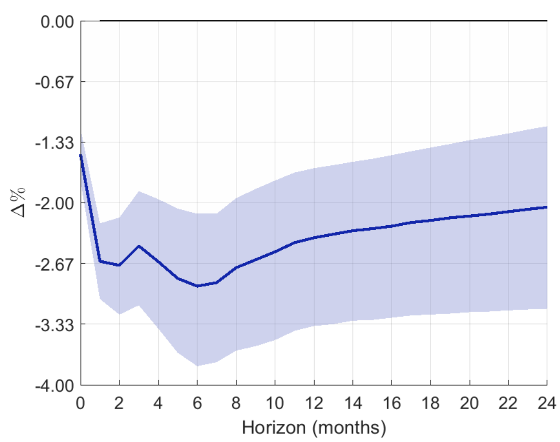
(d) Investments



(e) Industrial Production

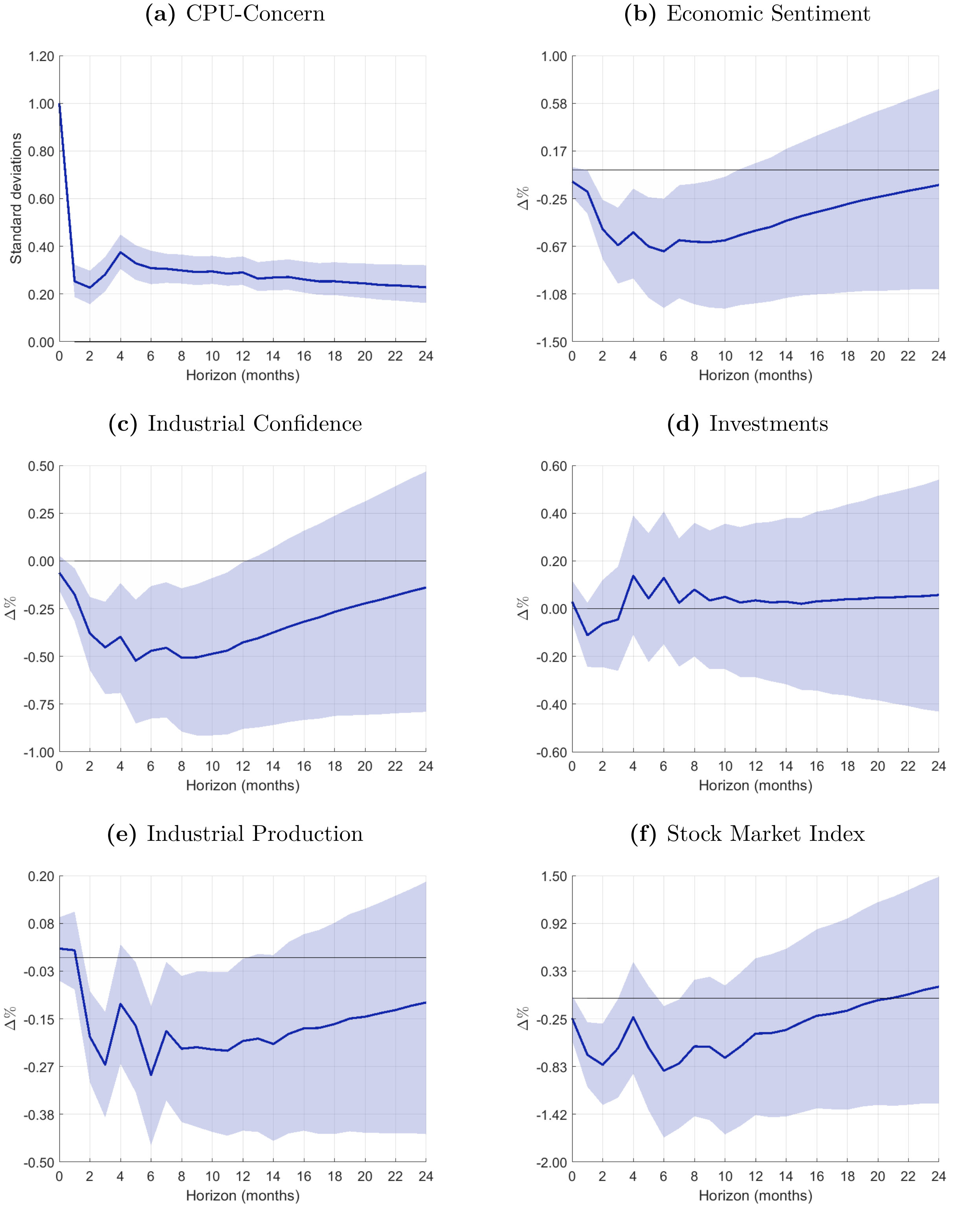


(f) Stock Market Index



Note: Shaded areas represent 68% HPDs. Total uncertainty is expressed in standard deviation terms, while the other variables are expressed in percentage change.

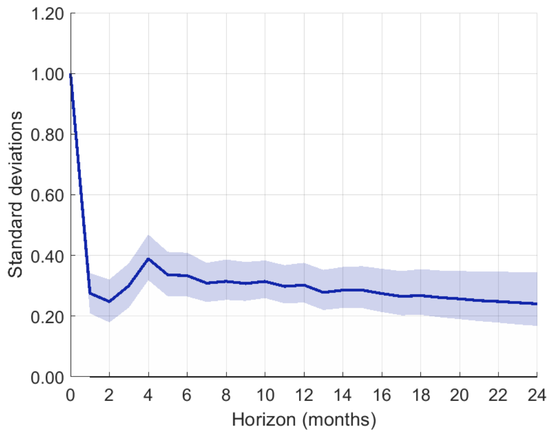
Figure A.5: IRFs with Covid Prior



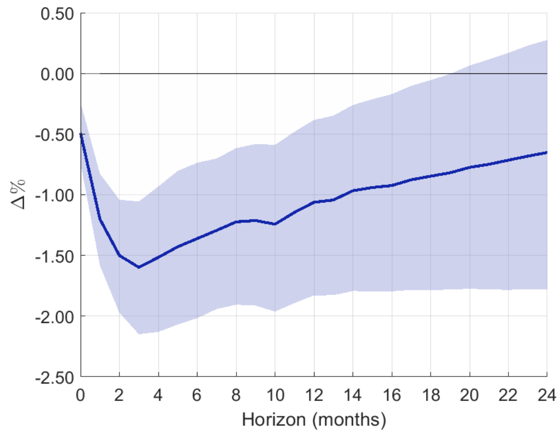
Note: Shaded areas represent 68% HPDs. CPU-Concern is expressed in standard deviation terms, while the other variables are expressed in percentage change.

Figure A.6: IRFs Only Economic Sentiment

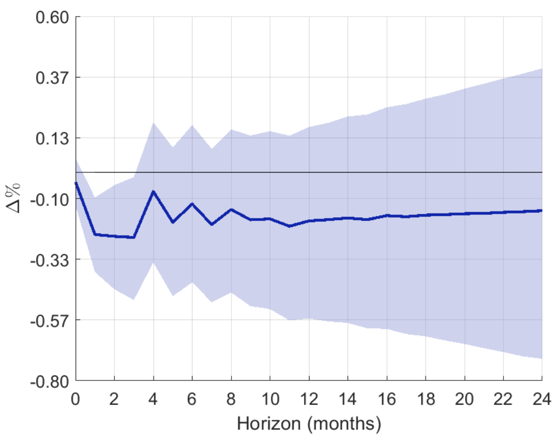
(a) CPU-Concern



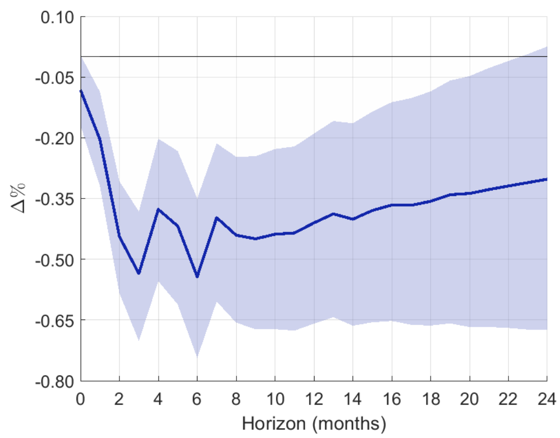
(b) Economic Sentiment



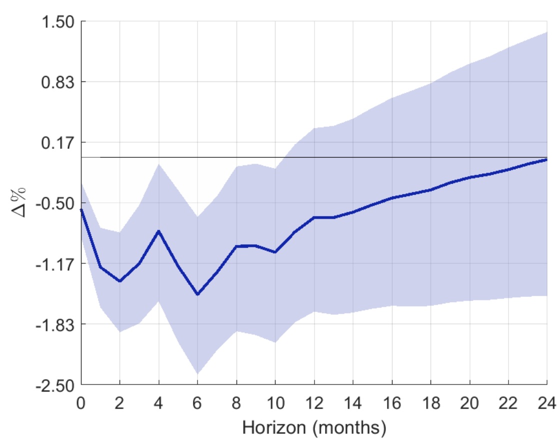
(c) Investments



(d) Industrial Production



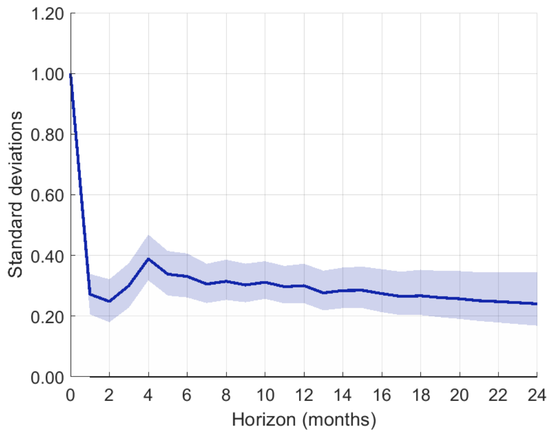
(e) Stock Market Index



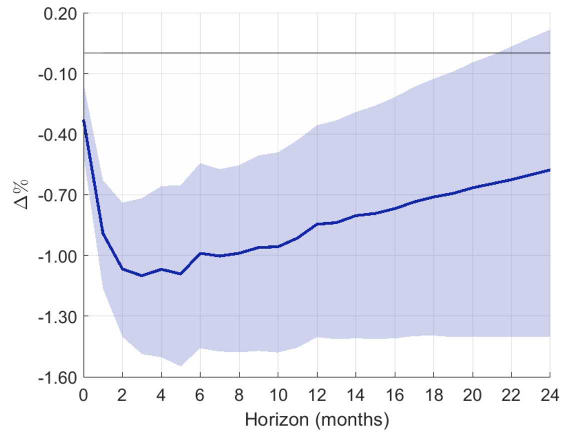
Note: Shaded areas represent 68% HPDs. CPU-Concern is expressed in standard deviation terms, while the other variables are expressed in percentage change.

Figure A.7: IRFs Only Industrial Confidence

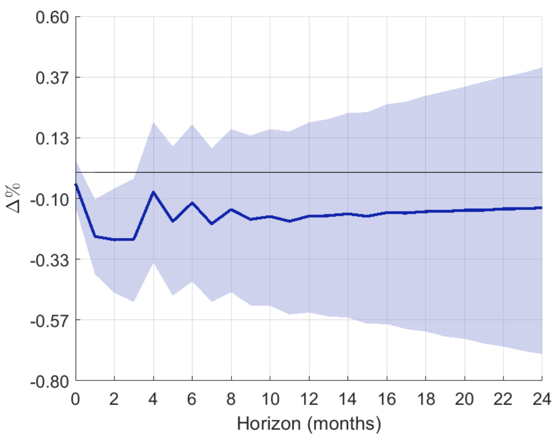
(a) CPU-Concern



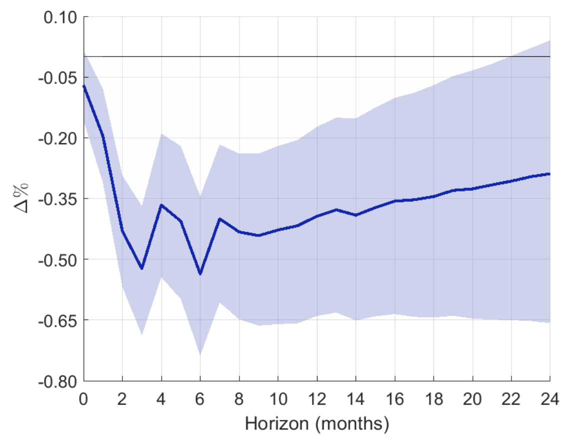
(b) Economic Sentiment



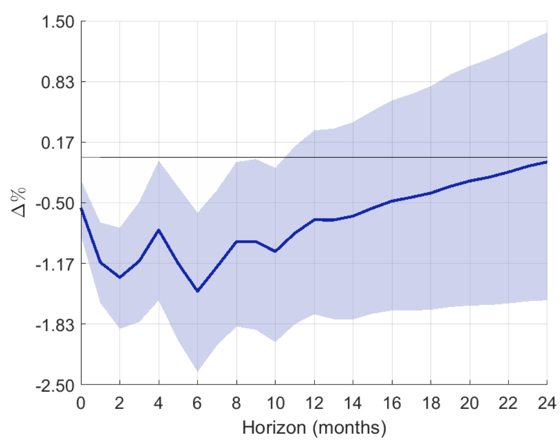
(c) Investments



(d) Industrial Production



(e) Stock Market Index



Note: Shaded areas represent 68% HPDs. CPU-Concern is expressed in standard deviation terms, while the other variables are expressed in percentage change.

DeNederlandscheBank

EUROSYSTEEM

De Nederlandsche Bank N.V.
Postbus 98, 1000 AB Amsterdam
020 524 91 11
dnb.nl