International Comparison of Climate Change News Index with an Application to Monetary Policy*

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December 15, 2023

Abstract

We construct a Climate Change News (CCN) index which measures attentions to climate change risk for Japan, based on text information from newspaper articles. Our index is compared with the original WSJ Climate Change News index of Engle et al. (2020) for the U.S. (WSJ-CCN index), as well as other measures of macroeconomic uncertainty. We find that our CCN index for Japan is more correlated with the WSJ-CCN index than the other macroeconomic uncertainty measures in Japan. We also find that, for both Japan and the U.S., CCN index has significantly negative effects on economic sentiment, but has ambiguous effects on industrial production. This contrasts the fact that macroeconomic uncertainty measures have negative effects on both economic sentiment and industrial production. As an application of the CCN indexes, we investigate if the effectiveness of monetary policy can depend on the degree of attention to climate change risks.

JEL Classification: E32, E52, Q54

Keywords: Climate Change; Text Analysis; Monetary Policy; Non-linear Local Projection

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*The authors would like to thank Jouchi Nakajima, participants of the CEBRA Annual Meeting 2022, the 2022 JEA Autumn Meeting, and the staff of the Bank of Japan for their valuable comments. The views expressed in this paper are those of the authors and do not necessarily reflect the official views of the Bank of Japan.

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1 Introduction

Climate change has been at the forefront of academic and policy debates. A growing body of literature has explored the impacts of climate change on the real economy, such as rising temperature or sea level and increasing frequency of extreme weather events (Burke et al. (2015), Colacito et al. (2019), Kim et al. (2022)). Climate change also has significant impacts on the financial markets (Ortega and Taşpınar (2018), Alok et al. (2020), and Addoum et al. (2023)). More recently, the relationship between climate change risk and financial markets is discussed, as in Engle et al. (2020), Krueger et al. (2020), and Bua et al. (2022). However, there is little empirical studies on the impact of uncertainty/risk related with climate change on the real economy.

The recent literature finds that uncertainty has significant impacts on the real economy, pioneered by Bloom (2009).[1] Some papers argue that increases in uncertainty related with economic policies, which is called Economic Policy Uncertainty (EPU), negatively affects the real economy (Baker et al. (2016), Caldara et al. (2019), and Husted et al. (2020)). As in Jurado et al. (2015), Scotti (2016), and Redl (2020), macroeconomic uncertainty (MU) has a detrimental effect on the real economy. In addition, the financial market volatility (VI) adversely influences the real economy (Bloom (2009), Bonciani and Ricci (2020) and Ludvigson et al. (2021)). However, there is a lack of understanding regarding the impacts of uncertainty/risk associated with climate change on the real economy.

This paper aims to fill these gaps. We ask how increasing uncertainties/concerns related to climate change affect the real economy. To this end, following Engle et al. (2020), we construct a Climate Change News (CCN) index which measures attentions to climate change risk for Japan, based on text information from newspaper article. Engle et al. (2020) extract a climate news series using text analysis based on the Wall Street Journal and build the index of attention to climate change for the US. We apply their contributions to Japan and measure the extent to which the climate change risks are paid attention in Japan. Based on the indexes, we statistically investigate the link between climate change uncertainty/risk and the real economy.

The main contributions of this paper are twofold. First, we investigate the statistical properties of the CCN indexes. Focusing on the US and Japan, we compare the indexes

[1] Bloom [2014] stresses that uncertainty is "a broad concept, including uncertainty over the path of macro phenomena ..., micro phenomena ..., and noneconomic events like war and climate change."

with three uncertainty-related indexes which are extensively used in the uncertainty literature: EPU, MU, and VI. Second, we examine the impacts of changes in the CCN indexes on the real economy. with particular focus on economic sentiment and industrial production. Some theoretical studies pay attention to the expectations channel through which the expectations about climate change have an impact on the real economy (e.g. Dietrich et al. (2021) and ECB (2021)). The intuition is simple. An increase in probabilities of disaster related to climate change is bad news for people, and thus this news depresses current economic activity. We aim to empirically test the theoretical implications of this channel.

In addition, as an application of the CCN indices, we examine how the attention to climate change risks influences the transmission of monetary policy shocks. We apply the local projection method developed by Jordà (2005). Departing from Jordà (2005), the key feature of our approach is to introduce a smooth regime switching between a regime of high and low attention to climate change risks. In this model, the transmission mechanism of monetary policy shocks is potentially allowed to change depending on the state of the attention to climate change risks. Hence, we can estimate the regime dependent impact of monetary policy shocks

Our main findings are as follows:

- the CCN index for Japan is more correlated with the WSJ-CCN index than the other macroeconomic uncertainty measures in Japan.
- For both Japan and the U.S., the CCN index has significantly negative effects on economic sentiment, but has ambiguous effects on industrial production. This contrasts the fact that macroeconomic uncertainty measures have negative effects on both economic sentiment and industrial production.
- The transmission of monetary policy becomes weaker as the climate change risk becomes higher. In other words, responses of economic activity and inflation become significantly weaker as the climate change risk becomes higher, for both the US and Japan.

Contact with the literature

Many studies empirically find that climate change affects the economy. For example, Burke et al. (2015) use panel data for 166 countries and show that there is a nonlinear relationship between annual temperature and productivity growth. Colacito et al. (2019) conduct a panel analysis using U.S. state- and sector-level data and find a statistically significant negative relationship between summer temperature and GDP growth. Dell et al. (2014) review the empirical studies which examine how climate variables such as temperature, precipitation, and windstorms influence economic outcomes.

Several studies focus on the impact of rare disasters including natural disasters on expectation formation. Barro (2006) and Gourio (2012) show that rare-disaster expectations could be an important driver of asset prices and the business cycle[2]. Isoré and Szczerbowicz (2017) estimate a New Keynesian model with a small time-varying probability of disaster. They show that even without the occurrence of disaster, an increase in its probability decreases consumption and wages. They argue that this effect can be interpreted as a shift in agents' degree of patience.

Expectations of natural disasters due to climate change are an example of rare-disaster expectations. Dietrich et al. (2021) conduct a survey in the U.S. to measure expectations about the economic impact of climate change. They find that the respondents change their expectations with various factors including media consumption and tend to assign large probabilities to natural disasters. They also calibrate a New Keynesian model with rare disasters and show that disaster expectations can lower the natural rate of interest. Motivated by these theoretical papers, we empirically confirm the mechanism and quantify how monetary policy transmission is affected.

This paper also contributes to a growing empirical literature that estimates state-dependent effects of fiscal and monetary policy shock. Auerbach and Gorodnichenko (2012) combine the local projection method of Jordà (2005) with a smooth regime-switching model to estimate the effects of fiscal policy during booms and recessions. Tenreyro and Thwaites (2016) construct the local projection model with regime-switches to study the efficacy of monetary policy shocks during booms and recessions. They find that monetary policy is less powerful during recessions. Falck et al. (2021) estimate the effects of monetary policy under high and low disagreement about inflation expectations. They show that a contractionary U.S. monetary policy shock leads to a statistically significant increase in inflation and inflation expectations in times of high disagreement, whereas in times of low dis-

[2] They define "rare-disaster" as an infrequent and large macroeconomic shock including not only natural disasters but wars or financial crisis.

agreement it leads to a significant decline in these variables. They also reconcile this result with a New Keynesian model which includes dispersed information. Departing from these papers, we focus on the attention to climate change.

The remainder of this paper is organized as follows. Section 2 presents the way to measure attention to climate change risks. In section 3, we conduct the statistical analysis of the CCN indexes. As an application of the CCN indexes, section 4 presents if the effectiveness of monetary policy can depend on the degree of attention to climate change risks. Finally, section 6 concludes with some thoughts for future research.

2 Climate Change News index

This section aims to describe how to construct the CCN index. First of all, we introduce the methodology developed in Engle et al. (2020). They propose the indexes to measure the attention to the climate change for the U.S. Next, we discuss how we apply their method to Japan.

2.1 Index Measuring climate change news: Engle et al. (2020)

Engle et al. (2020) propose the index measuring innovations in news on climate risk, which is called the the Wall Street Journal climate change news (WSJ-CCN) index. They construct the index extracting news on climate change by using textual analysis from the Wall Street Journal (WSJ). They follow three steps to develop the WSJ-CCN index.

First of all, they quantify the intensity of climate news coverage in the WSJ. To this end, they compare the news content to a corpus of climate change-related risks appeared in authoritative reports. More specifically, they refer to climate change white papers such as the Intergovernmental Panel on Climate Change (IPCC), the Environmental Protection Agency (EPA), and the U.S. Global Change Research Program. In addition to these white papers, they collect climate change reports published by the United Nations, NASA, the IPCC, the EPA, and others. They aggregate these text documents into a "Climate Change Vocabulary (CCV)." The CCV amounts to the list of unique terms and the frequency with which each term appears in the aggregated corpus. The list includes extreme weather events (e.g., floods, hurricanes, droughts, wildfires and extreme temperatures), physical changes to the planet (e.g., sea level changes, glacial melting and ocean temperatures), regulatory discussions, technical progress in alternative fuel delivery, and the price of fossil fuels.

Next, they make term frequency–inverse document frequency scores, that is $tf - idf$ scores, for the CCV. To this end, they create a list of term counts for the WSJ on a daily basis. Each edition of the WSJ is regarded as a "document," and term counts are calculated separately for each document. They convert these term counts into $tf - idf$ scores. tf means term frequency and is the count of occurrences of a term in a given document. If a term j is rare in a document i, the term j does not characterize the document i and $tf_{i,j}$ will be small. idf means inverse document frequency, which is the log of one over the share of documents containing a certain word. If a term j appears in most documents, it earns low idf_j because the term j is less informative about any individual document's content. The $tf - idf_{i,j}$ is calculated by multiplying $tf_{i,j}$ and idf_j for each term j and each document i. Therefore, the $tf - idf_{i,j}$ defines the most representative term in a given document to be those that appear infrequently overall, but frequently in that specific document.

Finally, they construct their daily climate change index as the "cosine similarity" between the $tf - idf$ scores for the CCV and each daily WSJ edition. Days in which the WSJ uses the same terms in the same proportion as the CCV earn an index value of one, while days in which the WSJ uses no words from the CCV earn an index value of zero. Approximately speaking, their raw WSJ Climate Change News (WSJ-CCN) Index describes the fraction of the WSJ dedicated to the topic of climate change each day, as defined by the texts that underlie the CCV. They scale this index by a factor of 10,000 to allow interpretation of the magnitudes of innovations in the index.

Figure 2 shows the WSJ-CCN index for the U.S. constructed in Engle et al. (2020). The WSJ-CCN index spikes when domestic or international climate events happened such as Copenhagen Accord in December 2009 and the publication of the Third National Climate Assessment in May 2014. It also indicates that the intensity of climate news coverage has steadily increased and remained high since the mid-2000s in the U.S. We use this WSJ-CCN indices to capture attentions to climate change risks in the U.S.[3]

[3]Engle et al. (2020) point out that this index is constructed under assumption that news about climate change are all bad news or related to risks. To justify this premise they also construct another index that is designed to focus on negative news about climate change. They confirm that both indices spike around salient climate events and indicated high correlation across these measures. In conclusion, they argue that both indices capture common elements of climate change risk.

2.2 Applying to Japan

We apply Engle et al. (2020) to extract the CCN index for Japan. We are based on textual news coverage in the Mainichi Shinbun newspaper articles from 1994 onward, which is one of the major newspapers in Japan, covering a wide range of Japanese and world news.[4] We also collect the Annual Report on the Environment, the Sound Material-Cycle Society and Biodiversity in Japan issued by the Ministry of the Environment from 1997 to 2021. The white papers cover a variety of topics, including industrial waste and biodiversity. Therefore, we extract the chapter on the climate change from the white papers. Appendix table 3 presents the full list of these authoritative texts. The collected documents consist of statements about climate change, such as the increase in natural disasters due to climate change and actions to mitigate climate change.

Following Engle et al. (2020), we construct our CCV for Japan from the climate change-related reports. Figure 1 provides an illustration of the CCV for Japan in the form of a word cloud. The term sizes are proportional to their frequency. The CCV are mainly composed of words such as ”environment” and “emissions,” which is consistent with Engle et al. (2020). These words would imply some kind of the physical risk like increase in extreme weather events. In addition, the CCV includes other aspects of the climate risk such as the transition risk. Terms such as “countermeasure”, “reduction”, and “implementation” are representative of the transition risk topic.[5]

Then, we make term frequency–inverse document frequency scores, that is $tf - idf$ scores, for the CCV. To this end, we create a list of term counts for the newspaper on a daily basis. Each edition of the Mainichi Shinbun is regarded as a “document,” and term counts are calculated separately for each document. We convert these term counts into $tf - idf$ scores. The $tf - idf_{i,j}$ is calculated by multiplying $tf_{i,j}$ and idf_j for each term j and each document i. Therefore, the $tf - idf_{i,j}$ defines the most representative term in a

[4]We also used data from Nikkei Shinbun to create a climate change attention index to check robustness. Like the Mainichi Shinbun, the Nikkei Shinbun also covers Japanese and world news, but has a relatively large number of articles related to financial markets and corporations. While the Mainichi Shinbun is a media sources mainly consumed by household, the Nikkei Shinbun is that consumed more by financial market participants. As discussed in more detail below, there are no major differences between the indices using the Mainichi Shinbun and the Nikkei Shinbun in Japan. Therefore, for the empirical analysis, we use an index based on the Mainichi Shinbun because it has a longer sample.

[5]Both Engle et al. (2020) and our study focus on climate change risks from a broad perspective and do not identify them in detail. In this regard, Bua et al. (2022) use a similar methodology to ours to extract physical and transition risks for the euro area, respectively.

given document to be those that appear infrequently overall, but frequently in that specific document.[6]

Next, as in Engle et al. (2020), we convert term counts of the CCV into $tf - idf$. We treat the CCV as a single document when calculating term frequencies ($tf_{CCV,j}$), and apply the inverse document frequency (idf_j) calculation from the newspaper corpus. Multiplying $tf_{CCV,j}$ and idf_j, we get the $tf - idf_{CCV,j}$ for each terms of the CCV.

Finally, we construct our daily index on the attention to climate change news as the cosine similarity between the $tf - idf$ vector for the CCV ($tf - idf_{CCV,j}$) and for each daily newspapers($tf - idf_{i,j}$). If the newspaper on a given day used the same terms in the same frequency as the CCV, an index value will be one, while if the newspaper on a given day used no terms in the CCV, an index value will be zero. This index can be regarded as the fraction of the articles dedicated to the topic of climate change each day, as defined by the texts that underlie the CCV. We take the monthly average of this index and scale it by a factor of 10000 to allow interpretation of the magnitudes of innovations in the index.

Figure 3 shows our CCN index, covering from January 1994 to December 2021. The thin line represents original series of the CCN index, and the solid line indicates six months backward moving averages of the original series. The index rose steeply when global climate treaties and major global conferences to prevent climate change were adopted. As is shown in next subsection, this is consistent with the indexes observed in the U.S.

As a robustness check, we use another Japanese major newspaper, Nikkei Shinbun, to construct CCN index. Appendix Figure 17 illustrates the developments of the CCN index from Nikkei. The figure indicates that the CCN indexes from both the Mainichi Shinbun and the Nikkei Shinbun increase in the same periods. Also, the correlation between the two CCN indexes is 0.79 so that our CCN index is robust in terms of the data source.

3 Statistical Analysis on Climate Change News index

In this section, we aim to clarify the statistical properties of the CCN indices, comparing the CCN indexes with three uncertainty-related indexes. We also investigate the impacts of changes in the CCN index on economic sentiment and industrial production, as well as three uncertainty measures.

[6] See Gentzkow et al. (2019).

3.1 Three measures on macroeconomic uncertainty

In this section, we compare the CCN indices with three uncertainty-related indexes which are commonly used in previous empirical studies on uncertainty in macroeconomics. First measure is the economic policy uncertainty indexes, called EPU, for the U.S. and Japan. The EPU for the U.S. is calculated by Baker et al. (2016), and Arbatli et al. (2022) estimate the index for Japan. These indexes reflect the frequency of articles in major newspapers that contain certain terms relevant to ”economy”, ”policies”, and ”uncertainty.” [7] The EPU is computed as the ratio of the number of articles that include at least one word listed in all three categories: “economy”, “policy”, and “uncertainty” to the total number of articles. It tends to spike during events that are ex-ante likely to cause increases in perceived policy uncertainty, such as debates over the stimulus package, the debt ceiling dispute, wars and financial crises.

Second index is the macroeconomic uncertainty indexes which measure uncertainty by computing the common factor of the time-varying volatility of the forecast errors from a large number of economic time series. This implies that they simply but comprehensively capture the uncertainty caused by various macroeconomic factors. For example, the macroeconomic uncertainty index for Japan rises sharply during not only economic downturn such as the Global Financial Crisis, but also other events like the Great East Japan Earthquake in March 2011. This index is developed by Jurado et al. (2015) for the U.S. and the index for Japan is estimated by Shinohara et al. (2020).

Finally, we utilize the stock market volatility index, used by Bloom (2009), as an indicator of uncertainty. It represents the degree of real-time implied volatility quantified by the financial markets. This implies that it would mainly capture the uncertainty in financial conditions as perceived by market participants. We use the VIX for the U.S. and Nikkei VI for Japan.

We pick up three uncertainty-related indices we discuss above, because there are extensive empirical literature on studying the statistical properties of these measures and thus these properties are well understood. Therefore, comparing the CCN indices with three measures, we can improve our understanding on how different the climate change related

[7] The number of newspapers used for the EPU is ten in the U.S. and four in Japan. The index for the U.S. includes USA Today, Miami Herald, Chicago Tribune, Washington Post, Los Angeles Times, Boston Globe, San Francisco Chronicle, Dallas Morning News, Houston Chronicle, and Wall Street Journal. For Japan, Asahi Shinbun, Nikkei Shinbun, Mainichi Shinbun, and Yomiuri Shinbun are used for calculation.

issues are from economic uncertainty.

3.2 Correlation among indices

First of all, we compute the correlations between the indexes, based on monthly measures.[8] Table 1 summarizes the correlation coefficients for each pair. The upper table presents the results for Japan. Three findings are worth noting. First, looking at the first column of the upper table, we know that the correlations between the CCN index and other macroeconomic uncertainty measures are significantly positive. Specifically, the correlation of the CCN index with EPU is 0.23, and the correlation with macro uncertainty and stock market volatility index are 0.26 and 0.19 respectively. Second, more importantly, the correlation between the CCN index and the WSJ-CCN index is 0.45. Therefore, the CCN index is more correlated with the WSJ-CCN index than other macroeconomic uncertainty measures for Japan. Thirdly, the correlations among other macroeconomic uncertainty measures are significantly positive and higher than the correlations of other macroeconomic uncertainty measures with the CCN index, except for the correlation between EPU and macro uncertainty. The correlation coefficient between EPU and macro uncertainty is 0.25, which is comparable to the correlation of the CCN index with other uncertainties. However, the correlation between EPU and volatility index is 0.53, and the correlation between macro uncertainty and volatility index is 0.49, which implies both are higher than the correlation of the CCN index with other uncertainties.

Looking at the results for the U.S. (the lower table), we also know the same implications as Japan. The WSJ-CCN index has the largest correlation with the CCN. The correlation between the WSJ-CCN index and macro uncertainty is 0.18, although the correlations of the WSJ-CCN index with other two measures of uncertainty are not significant. In addition, the correlation coefficient between the EPU and the macro uncertainty index is 0.27, and correlations of volatility index with EPU and macro uncertainty are 0.45 and 0.58, respectively, which indicates that the correlations among uncertainty measures tend to be significantly high relative to the WSJ-CCN index.

To check whether there is a prior-lagging relationship in the CCN index and the WSJ-CCN index, we calculate the cross correlations between them. We find that there is no prior-lagging relationship between the attention to climate change risk for Japan and the

[8] The results are robust when using quarterly data in both Japan and the U.S..

U.S.. Figure 4 shows the results of calculating the cross correlations between them. It is worth noting that the correlation coefficients are the largest when there is no time lag and the cross correlations are symmetric around lag zero. Therefore, the CCN index and the WSJ-CCN index moves similarly in response to some events related to climate change.[9]

To wrap up, the results discussed above suggest that climate change concerns are driven by the common factor in Japan and the U.S such as salient global climate events or global trends of discussion on climate change risks. In addition, the developments of attention to climate change risks are different from other macroeconomic uncertainties.

3.3 Impacts on sentiment and economic activity

We aim to investigate the impacts of the CCN indices on the macroeconomy, comparing those of other uncertainty measures.

In particular, we focus on the effects on the economic sentiment and the industrial production. The economic sentiments of the U.S. are estimated by Shapiro et al. (2022), and UTEcon also assesses the sentiment for Japan.[10] Both are developed by extracting sentiment from economic and financial newspaper articles using textual analysis. Shapiro et al. (2022) point out that the news sentiment has a predictive power of movements of survey-based consumer sentiment and their developments can affect on real variables such as consumption and output.

3.3.1 Correlations with sentiment and industrial production

The upper of Table 2 shows the correlation coefficients for Japan. What is worth noting are twofold. First, the correlation between the CCN index and economic sentiment is significantly negative, although the correlations of the CCN index with industrial production is not significant. Second, however, the correlations of macroeconomic uncertainty measures with economic sentiment and industrial production have significantly negative. The correlation between the news sentiment and EPU, macro uncertainty, and stock market

[9]There is still room for further scrutiny, including comparisons based on higher frequency data such as weekly or daily rather than monthly data. Furthermore, trends in another countries, such as Europe, can be influencing the attention to climate change risks in the U.S. and Japan

[10]See the website of UTEcon.

volatility index are -0.59, -0.34 and -0.63 for Japan,. In addition, the correlation of industrial production with EPU, macro uncertainty and stock market volatility are -0.12, -0.24 and -0.28.

Looking at the lower of Table 2, we know that the two findings discussed above are also true for the U.S.. Therefore, it could be stressed that the CCN indices, as well as other uncertainty measures, negatively correlates with economic sentiments. On the other hand, at least in the short-run, there are no obvious relation between attention to climate change and industrial production, which contrasts the fact that other uncertainty measures have significantly negative correlations with industrial production.

3.3.2 VAR

The implications discussed above also hold in a structural vector autoregressive framework. To see this, we investigate how the CCN index and other uncertainty indices affect the news sentiment and industrial production. Following a literature relying on recursively identified structural VAR models such as Basu and Bundick (2017), and Bekaert et al. (2013), and Caggiano et al. (2014), the our benchmark VAR model is collected in the vector the vector $X_t = [a_t, b_t]$, where a_t represents industrial production or economic sentiment. b_t stands for one of uncertainty measure or the CCN indices. We estimate the bivariate recursively identified structural VAR models as follows:

$$X_t = BX_{t-1} + C\epsilon_t, \tag{1}$$

where ϵ_t refers to structural shocks. a_t is ordered after real activity variables in our VAR model.

Figure 5 lays out the responses of the news sentiment or industrial production to one standard deviation shocks to the CCN index or other uncertainty measures for Japan. As is shown in the figures, the news sentiment is significantly decreased after increases in uncertainty measures and the CCN index. On the other hand, with respect to industrial production, the uncertainty measures have significantly negative impacts on industrial production, consistent with the findings of Bloom (2009), although the CCN index has ambiguous impacts on industrial production.

Figure 6 shows the results for the U.S. data. The implications are also true for the U.S..

The response of industrial production to the CCN index in panel (a) is not significant, although increases in uncertainty measures have significant negative impacts on industrial production. Therefore, there is a clear difference between the CCN index and other uncertainty indices in terms of their impact on the industrial production, but not on economic sentiment. These results imply that, while the attention to climate change risks can exacerbate economic sentiment, it does not necessarily lead to an immediate stall of economic activity.[11]

Local Projection framework

We also estimate a bivariate Local Projection using the same variables as follows

The estimation results are shown in . The impulse responses from the Local Projection are consistent with the VAR results with respect to uncertainty measures. An increase in the macroeconomic uncertainty or stock market volatility significantly reduces industrial production in the U.S.. In addition, for both Japan and the U.S., CCN index has significantly negative effects on economic sentiment. However, the impulse responses to increases in the CCN index have differenct implications from the VAR results. Increases in the CCN indexes have significantly negative impacts on industrial production for the U.S. and Japan. These results indicates that the CCN indexes has ambiguous effects on industrial production.

To wrap up this section, what is worth noting are twofold. First, our CCN index for Japan is more correlated with the WSJ-CCN index than the other macroeconomic uncertainty measures in Japan. Second, We also find that, for both Japan and the U.S., CCN index has significantly negative effects on economic sentiment, but has ambiguous effects on industrial production. This contrasts the fact that macroeconomic uncertainty measures have negative effects on both economic sentiment and industrial production.

4 Application of the CCN indexes

This section presents our empirical approach to estimate how the attention to climate change risks influences the transmission of monetary policy shocks. To quantify it at hand, we apply the local projection method developed by Jordà (2005). Departing from Jordà

[11]They are robust to estimating three-variable VARs using industrial production, News Sentiment, and each uncertainty index, as well as to changing the order of the variables in the VAR models.

(2005), the feature of our approach is to allow smooth regime-switches, following Auerbach and Gorodnichenko (2012) and Tenreyro and Thwaites (2016). The regime is identified by the attention to climate change risks in our estimation. Based on this model, the transmission mechanism of monetary policy shocks is potentially allowed to change depending on the state of the attention to climate change risks. In what follows, we describe our econometric model and the data sources.

4.1 Econometric Methodology

To examine how the attention to climate change risks affects the transmission of monetary policy, we extend the local projection model by Jordà (2005) to introduce a smooth regime-switching mechanism as follows:

$$y_{t+i} = \tau_i t + (\alpha_i^H + \beta_i^H \epsilon_t + \gamma_i^H \boldsymbol{x}_t) F(z_t) + (\alpha_i^L + \beta_i^L \epsilon_t + \gamma_i^L \boldsymbol{x}_t)(1 - F(z_t)) + u_t \tag{2}$$

where $i \in [0, I]$ indicates the number of periods after the shock hits the economy. A time trend ($\tau_i t$) is included. We control for regime-specific constants α_i^λ, regime-dependent effects of the monetary policy shock β_i^λ, and a set of regime-specific coefficients γ_i^λ for the vector of control variables $\boldsymbol{x}_t$. We include the industrial production, consumption, firms' capital investments, consumer price and corporate bond spreads as controls. We use corporate bond spreads as a control variable because it could be a source of business cycle fluctuations (Gilchrist and Zakrajšek (2012))[12]. $\lambda = H, L$ refers to the high (H) and low (L) attention regime, respectively. The regression residual is denoted by u_{t+i}.

The regimes are identified with the regime-indicating variable z_t. z_t represents six months backward moving averages of the CCN Index, reflecting the level of the attention to climate change risks. The continuous function $F(z_t)$ has the following logistic function:

$$F(z_t) = \frac{\exp\left(\theta \dfrac{z_t - c}{\sigma_z}\right)}{1 + \exp\left(\theta \dfrac{z_t - c}{\sigma_z}\right)} \tag{3}$$

where c corresponds to the mean and σ_z to the standard deviation of z_t. The function is increasing in z_t. The parameter θ determines the curvature of $F(z_t)$ and, hence, how

[12]Bu et al. (2021) adds excess bond premium to their VAR model for the same reason.

strongly the probability function reacts to changes in attention to climate change risks. Previous studies did not estimate the degree of regime-switching but calibrated it (Auerbach and Gorodnichenko (2012); Tenreyro and Thwaites (2016); Falck et al. (2021)). We follow these literature and use a value of $\theta = 5$. However, our results are robust to a wide range of values as mentioned in the section 4.4.

To estimate impulse responses, we use local projections which provide a direct estimate of the response of the dependent variable i periods after the shock ϵ_t, depending on whether the economy is in a high- or low-attention regime when the shock hits. The estimation of Eq.(1) is repeated for each horizon i and the set of β_i^λ reflects the impulse response function for y_t within the I periods.

By introducing $F(z_t)$, it is allowed that there are two regimes with respect to the attention to climate change risks and these regimes are characterized by potentially different macroeconomic dynamics. The responses of the endogenous variables, y_{t+i}, to a monetary policy shock ϵ_t depending on the probability of being in the high- or low-attention to climate change risk regime, $F(z_t)$. Hence, the effects of monetary policy shocks are potentially conditioned on the probability to be in a high or low-attention regime.

In addition, our approach also captures potential regime switches after the shock. The empirical model controls for the probability of being in the high-climate risk attention regime when the shock occurs but makes no assumptions about the state of the economy in subsequent periods. If attention to climate change risk responds to the shock or the economic conditions, this would implicitly be captured in the estimated coefficients.

We estimate the econometric model for the U.S. and Japan separately. Comparing the estimation results in the U.S. with Japan, we could examine the robustness or the difference across two countries.

In our benchmark specification, the control variables are twelve lags in the U.S. and seven lags in Japan, determined by AIC. The results are unchanged when we change lag length of the control variables as mentioned in section 4.4.

4.2 Data

We use monthly data for the U.S. and Japan. As mentioned above, the data includes the industrial production, consumption, firms' capital investments, consumer price and corporate bond spreads. The estimation periods cover from October 1997 to December

2019 because of corporate bond spreads availability. We exclude 2020 because COVID-19 affected economies dramatically and it might distort our estimation.

Price index for the U.S. is PCE deflator excluding food and energy, although we use consumer price index (CPI) excluding fresh food and energy for Japan. We use manufacturers' value of shipments (nondefense capital goods excluding aircraft) for the U.S. and domestic shipments and imports of capital goods for Japan as firms' capital investments. The index of consumption is PCE for the U.S. and retail sales value for Japan. Indices for industrial production, price, firms' capital investment and consumption are three months moving averages for smoothing. The corporate bond spreads are ICE BofA US High Yield Index (option-adjusted spread) for the U.S. and BBB-rated corporate bonds spreads for Japan. We take the logarithm of the indices other than corporate bond spreads.

With respect to monthly monetary shocks, we use the exogenous monetary policy shocks as is common in the literature. We follow Bu et al. (2021) for the U.S. and Kubota and Shintani (2022) for Japan. Both papers develop shock series which stably bridge periods of conventional and unconventional monetary policy. These series are largely unpredictable from available information on the economy, and contain no significant central bank information effect. Hence, cleaner inference on the transmission of exogenous monetary policy shock is allowed.

4.3 Results

4.3.1 Identifying periods of high and low attention to climate change risks

Figure 9 and Figure 10 show $F(z_t)$, the probability of being in a regime with high attention to climate change risks, for the U.S. and Japan respectively. It should be highlighted that regimes have repeatedly switched over the sample period. This indicates that the model which preserves the degree of freedom of regime-switching is more suitable than the model in which regime changes are not allowed.

More specifically, the probability of being in low attention regimes is relatively high throughout the first half of the sample period both in the U.S. and Japan. However, the probability of being in a high attention regime has become higher after mid-2000s both in the two countries. This implies that more people have become concerned about climate change risks in recent years. In addition, unlike the U.S., a probability of being in a high attention regime is high between 1998 and 2002 in Japan. This is because Japan held the

Kyoto Protocol and more Japanese had been paying more attention to climate change risks in those period.

4.3.2 The regime-dependent transmission of monetary policy shocks

Figure 11 and Figure 12 show the impulse responses of industrial production, consumer price, firms' capital investment, and consumptions to a expantionary 100 basis points monetary policy shock in the U.S. and Japan respectively. The upper rows of Figure 11 and Figure 12 show the results of the linear model that is estimated without assuming regime changes, which implies that state-dependent effects are not considered. On the other hand, the lower panels of both figures show the results of our regime-switching approach. The responses in the regimes with high and low attention to climate-change risks are presented. The red solid lines represent the impulse responses in the high attention regime, and the blue dotted lines imply the responses in the low attention regime.

To start with, the upper panels of Figure 11 and Figure 12 indicate that all variables are significantly increased by an expantionary monetary policy shock. This is consistent with the implications of standard New Keynesian models and related empirical studies.

Turning to the lower panels in these figures, what is worth noting are twofold. First, the responses in the high climate change news regime are significantly different from those in the low climate change news regime. This implies that the transmission of monetary policy shocks is regime-dependent, and the extent to which climate change risks considered plays an important role in propagating monetary policy shocks.

Second, the transmission of monetary policy becomes significantly weaker in the regime of high attention to climate change risk. More specifically, the responses to the monetary policy shocks in a low attention regime are almost same as the responses of the linear model. In other words, all variables are significantly increased in the low attention regime in response to expantionary monetary policy shocks. Figure 11 shows that, after twenty months, the industrial production significantly increases by about 0.01 percentage points and the inflation rate also rises about one percentage points in the U.S. On the other hand, the responses of all variables to expantionary monetary policy shocks in a high climate change news regime are not significant, which implies that the transmission of monetary policy becomes weaker[13].

[13] Some empirical papers explore if economic uncertainty alters the monetary policy effectiveness (Aastveit

This is also true for Japan. The lower panels of Figure 12 show the responses to an expantionary monetary policy shock in the regime with high and low attention to climate change risks in Japan. The first column shows that the response of industrial production significantly increases by about 0.03 percentage points after twenty period in a low-CCN regime. In contrast, the response is insignificant in a high-CCN regime. On the third and fourth columns, the responses of firms' capital investment and consumption in a low climate change news regime (red solid lines) are statistically significant. However, the responses in a high-CCN regime (blue dotted lines) is small and statistically insignificant.

The lower panels of Figure 11 and Figure 12 also indicate that the responses of almost all variables are statistically different in the regime of high and low attention to climate change risk in both the U.S. and Japan.

4.4 Robustness check

The robustness of the application is assessed along several dimensions. We examine three types of exercises to check if our results are robust or not: alternative choices of the intensity of regime-switching θ, lags of control variables, and smoothness of regime variable.

First exercise is to show that our results are robust with respect to the choices of θ. To this end, we re-estimate the regressions with different value of θ. θ determines the intensity of regime-switching and we set $\theta = 5$ in the baseline specification. Figure 13 for the U.S. and Figure 14 for Japan show how the results are changed when we set θ to three or eight. In both figures, the responses to an expantionary monetary policy shock are well within the confidence bands of the baseline estimates, and regardless of different value of θ, the responses of all variables to monetary policy shocks tend to be weaker in high-CCN regimes compared to those in low-CCN regimes. It indicates that the baseline results are robust with respect to the intensity of regime-switching.

Second one is to examine if the results are robust when we change the lag length of control variables. The baseline regression Eq.(1) contains twelve lags of control variables for the U.S. and seven lags for Japan. As is discussed before, this lag structure is optimal as indicated by AIC. We re-estimate our model to check whether our results are robust or

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et al. (2017); Castelnuovo and Pellegrino (2018); Pellegrino (2021)). They employ non-linear structural VAR models and show that monetary policy shocks are less powerful when uncertainty is high. Aastveit et al. (2017) argues that the results are consistent with the hypothesis that agents gather more information and postpone decisions under high uncertainty, and this "wait-and-see" behavior makes them less responsive to changes in the economic environment such as interest rates.

not when we change the lag length. Figure 15 and Figure 16 show the impulse responses estimated in a regression model with the different lag structure for the U.S. and Japan, respectively. Figure 15 indicates that in the U.S., the impulse response is broadly in line with the baseline impulse response even when the length of the lag is changed, except when the lag of the control variable is short, such as the lag length is three. The estimation results using Japanese data in Figure 16 show that when the number of lags is twelve, the response of the inflation in the high-CCN regime deviates from the baseline. Otherwise, the results of the empirical analysis are robust with respect to the lag length of control variables in Japan.

Third and the last exercise is to check whether the results would vary if we change how long the CCN index was moving-averaged. They show that the qualitative message of the earlier analysis is unchanged in both the U.S. and Japan.

5 Conclusion

This paper statistically investigates the impacts of attentions to climate change risk on Japan and the U.S.. We find that, for both Japan and the U.S., the CCN index has significantly negative effects on economic sentiment, but has ambiguous effects on industrial production, which is not consistent the fact that macroeconomic uncertainty measures have negative effects on both economic sentiment and industrial production.

We apply the CCN indexes to investigate how changes in attentions to climate change risk alter the transmission of monetary policy. Out finding is that, if the effectiveness of monetary policy can depend on the degree of attention to climate change risksss.

For future research, we construct a model to interpret our empirical findings and provide some policy analysis. For example, we can include a mechanism of the transmission of transition risk in addition to physical risk. It can let us consider more channel of climate change risk. Another possible approach is that we apply a smooth transition VAR. It can let us investigate how the transmissions of structural shocks, such as demand and supply shocks, depend on the state of climate change risk.

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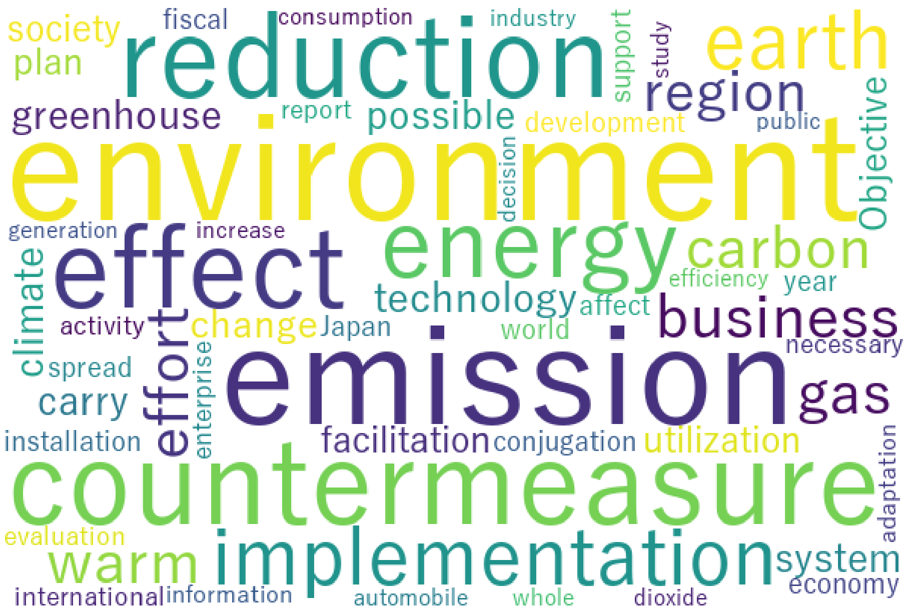

Figure 1: Climate change vocabulary in Japan.

Notes: Each word is originally in Japanese and is translated into English by Google Translation. Term sizes are proportional to their frequency in the corpus.

Table 1: Correlation coefficients

(a)Japan

	Climate Change News for Japan	EPU	Macro Uncertainty	Stock Market Volatility
Climate Change News for Japan	1.00 –			
EPU	0.23*** (3.94)	1.00 –		
Macro Uncertainty	0.26*** (4.49)	0.25*** (4.34)	1.00 –	
Stock Market Volatility	0.19*** (3.24)	0.53*** (10.43)	0.39*** (6.99)	1.00 –
WSJ-CCN	0.45*** (8.34)			

(b)the U.S.

	WSJ-CCN	EPU	Macro Uncertainty	Stock Market Volatility
WSJ-CCN	1.00 –			
EPU	0.06 (0.98)	1.00 –		
Macro Uncertainty	0.18*** (3.06)	0.27*** (4.64)	1.00 –	
Stock Market Volatility	-0.07 (-1.16)	0.45*** (8.38)	0.58*** (11.96)	1.00 –
Climate Change News for Japan	0.45*** (8.34)			

Notes: The upper number represents the correlation coefficient and the lower bracketed number represents the t-statistics. *** denotes statistical significance at the one percent level. Estimation period is from January 1994 to June 2017.

Table 2: Correlation with News Sentiment and Industrial Production

(a)Japan

	Climate Change News for Japan	EPU	Macro Uncertainty	Stock Market Volatility
News Sentiment	-0.20*** (-3.37)	-0.59*** (-12.36)	-0.34*** (-6.10)	-0.63*** (-13.56)
Industrial Production	-0.05 (-0.87)	-0.12** (-2.02)	-0.24*** (-4.22)	-0.28*** (-4.88)

(b)the U.S.

	WSJ-CCN	EPU	Macro Uncertainty	Stock Market Volatility
News Sentiment	-0.17*** (-2.81)	-0.61*** (-12.75)	-0.50*** (-9.56)	-0.53*** (-10.39)
Industrial Production	-0.05 (-0.81)	-0.24** (-4.09)	-0.49*** (-9.38)	-0.21*** (-3.57)

Notes: The upper number represents the correlation coefficient and the lower bracketed number represents the t-statistics. *** and ** denote statistical significance at the one percent and five percent levels, respectively. Estimation period is from January 1994 to June 2017. Industrial Production is converted to month-over-month.

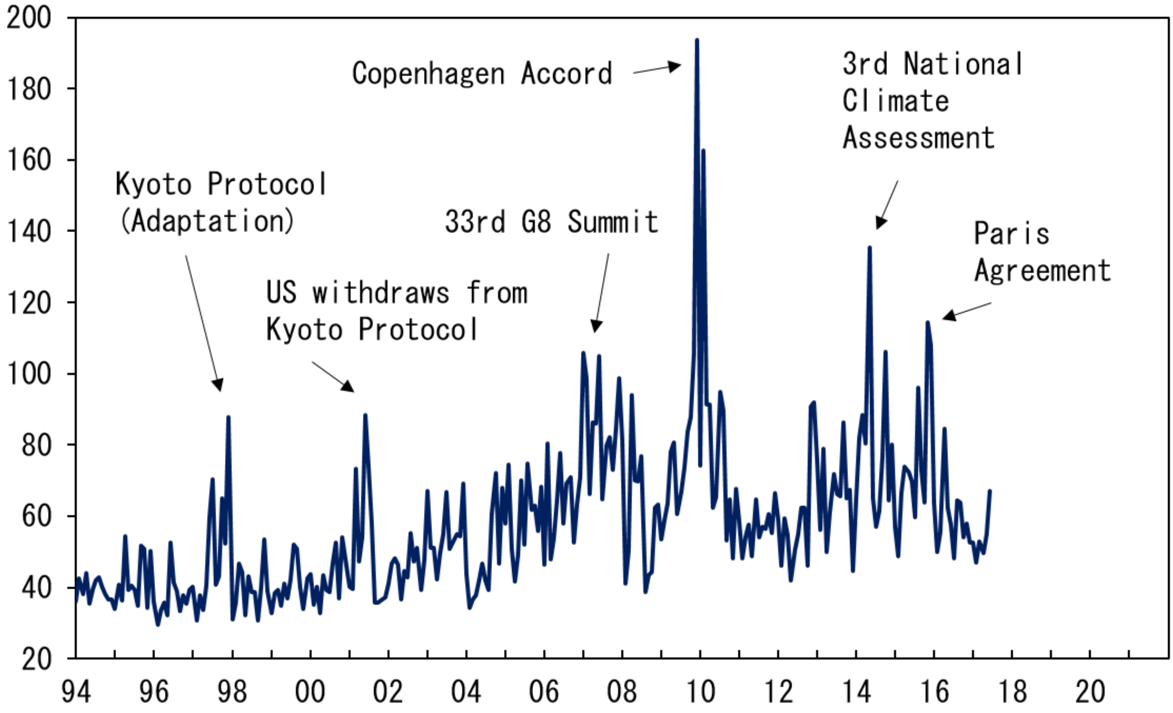

Figure 2: Climate Change News index in the U.S. (WSJ-CCN index)

Notes: This figure shows the U.S. Climate Change News index extracted from the WSJ, constructed by Engle et al. (2020). The unit of the vertical axis is a basis point.

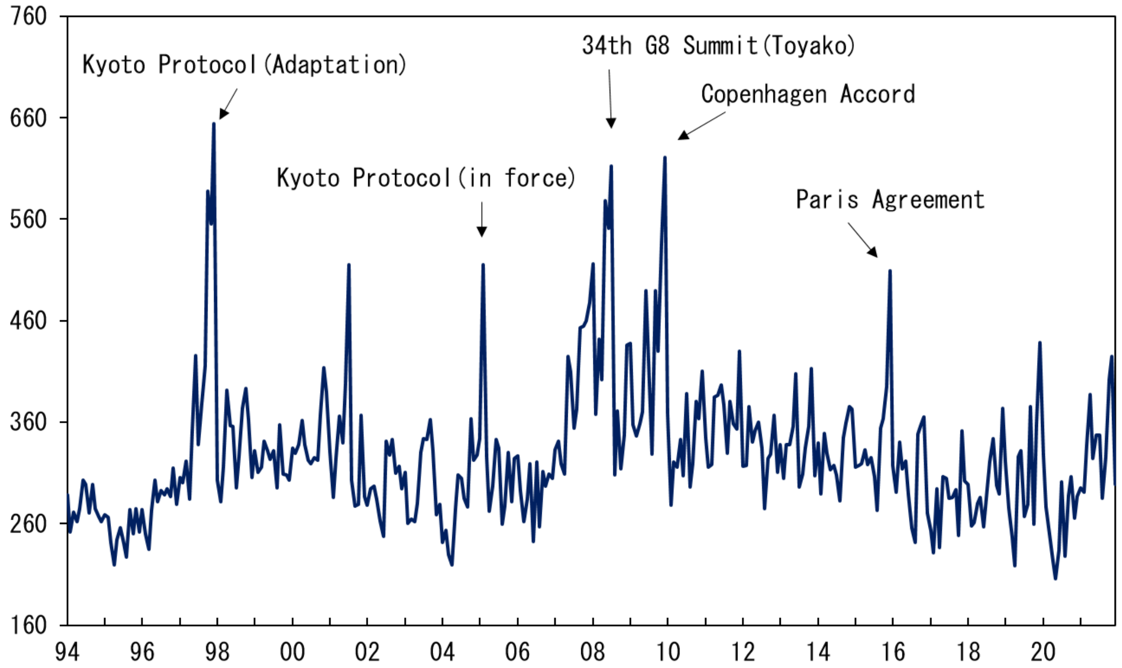

Figure 3: Climate Change News index in Japan.

Notes: This figure shows the Japanese Climate Change News index extracted from the Mainichi Shinbun. The unit of the vertical axis is a basis point.

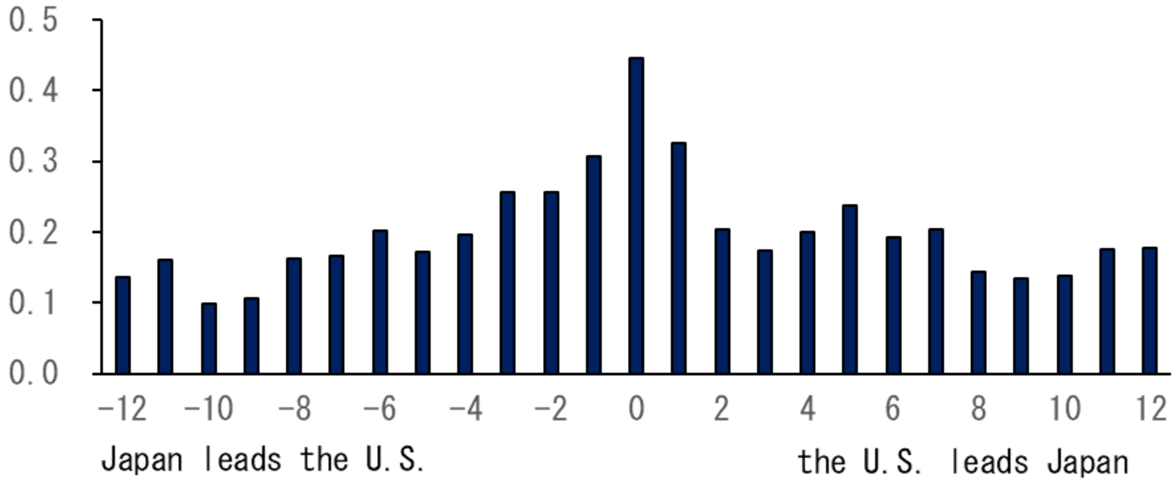

Figure 4: Correlation of Climate Change News index between Japan and the U.S.

Notes: The figure indicates correlation coefficients between the Climate Change News index in Japan and the U.S. under different lags. Estimation period is from January 1994 to June 2017.

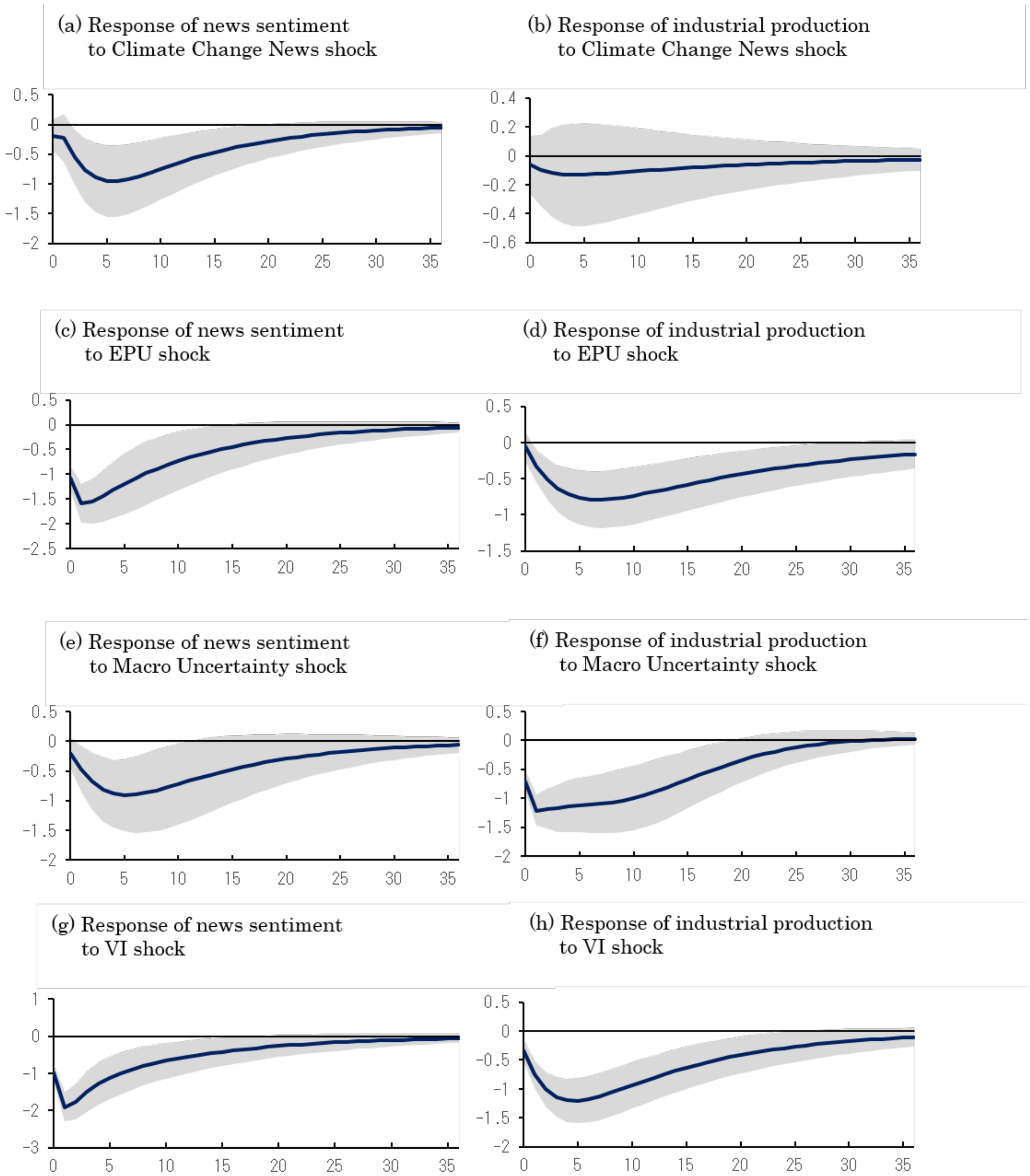

Figure 5: VAR impulse response in Japan

Notes: These panels show the impulse responses to one standard deviation shock from bivariate VAR. The sample period is from January 1994 to June 2017. The lag length in each VAR is set based on BIC. The shaded area indicates 95 percentile confidence bands.

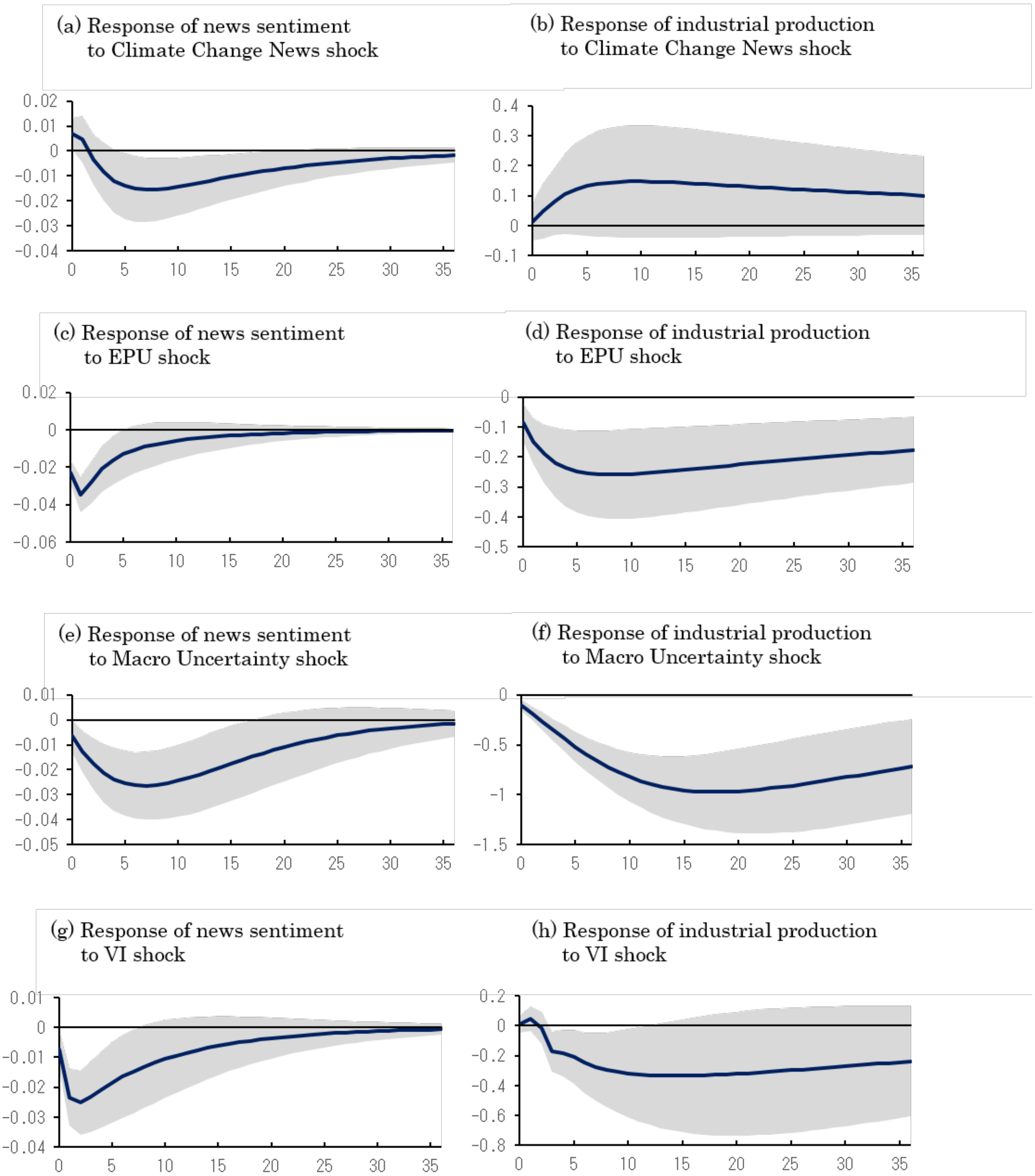

Figure 6: VAR impulse response in the U.S.

Notes: These panels show the impulse responses to one standard deviation shock from bivariate VAR. The sample period is from January 1994 to June 2017. The lag length in each VAR is set based on BIC. The shaded area indicates 95 percentile confidence bands.

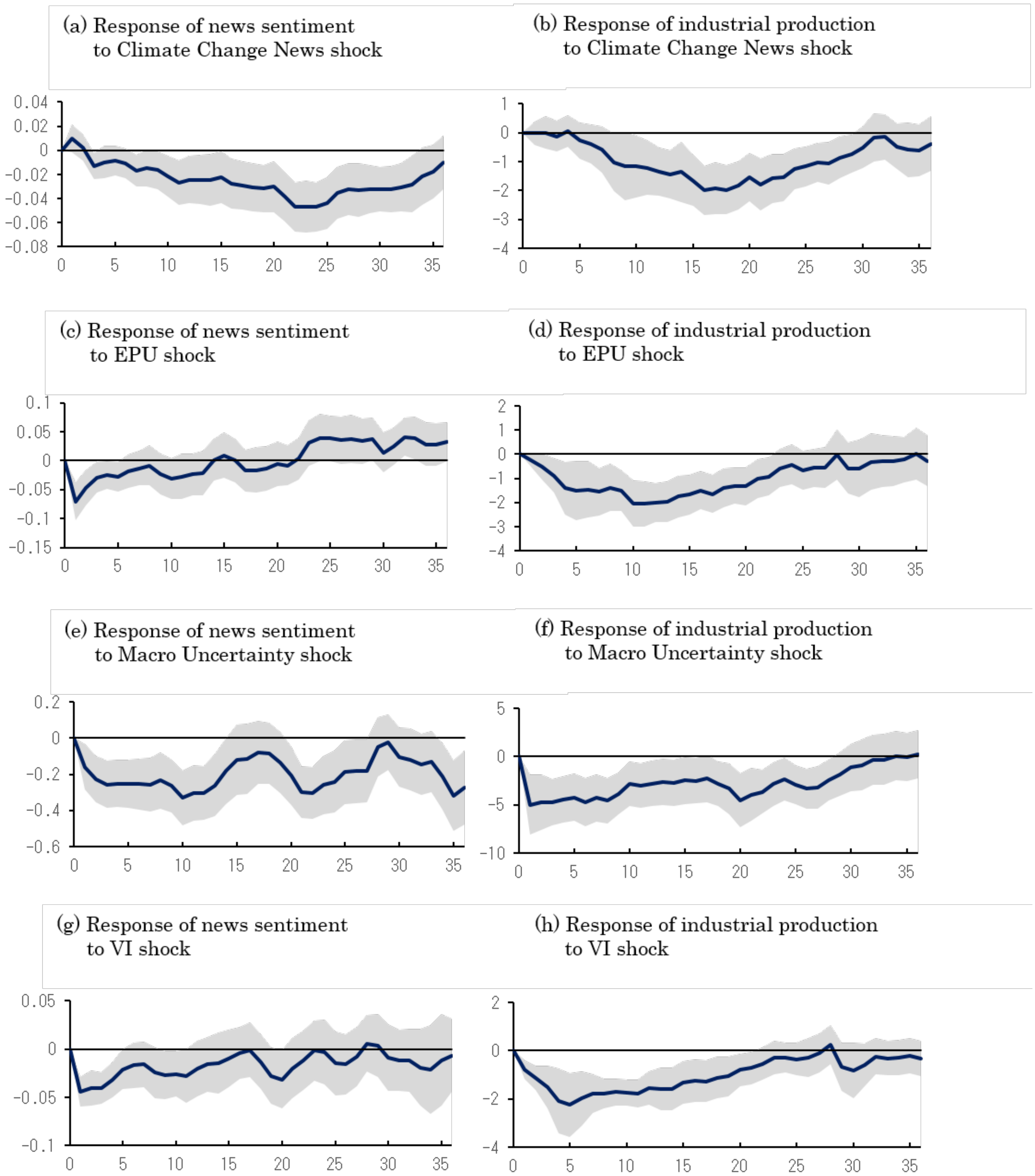

Figure 7: Local Projection impulse response in Japan

Notes: These panels show the impulse responses to one standard deviation shock from bivariate Local Projection model. The sample period is from January 1994 to June 2017. The lag length in each Local Projection model is the same with the VAR model. The shaded area indicates 95 percentile confidence bands.

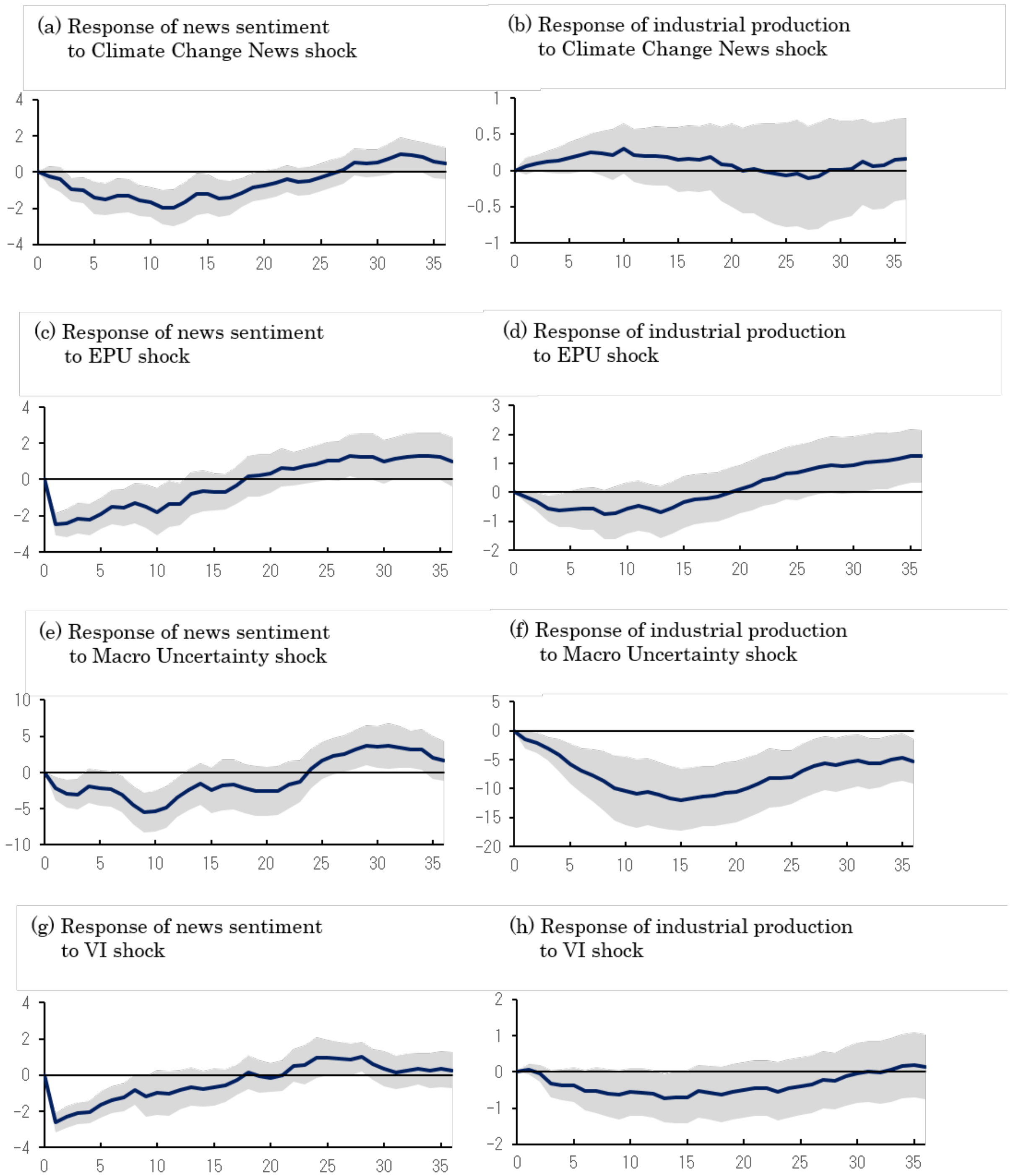

Figure 8: Local Projection impulse response in the U.S.

Notes: These panels show the impulse responses to one standard deviation shock from bivariate Local Projection model. The sample period is from January 1994 to June 2017. The lag length in each Local Projection model is the same with the VAR model. The shaded area indicates 95 percentile confidence bands.

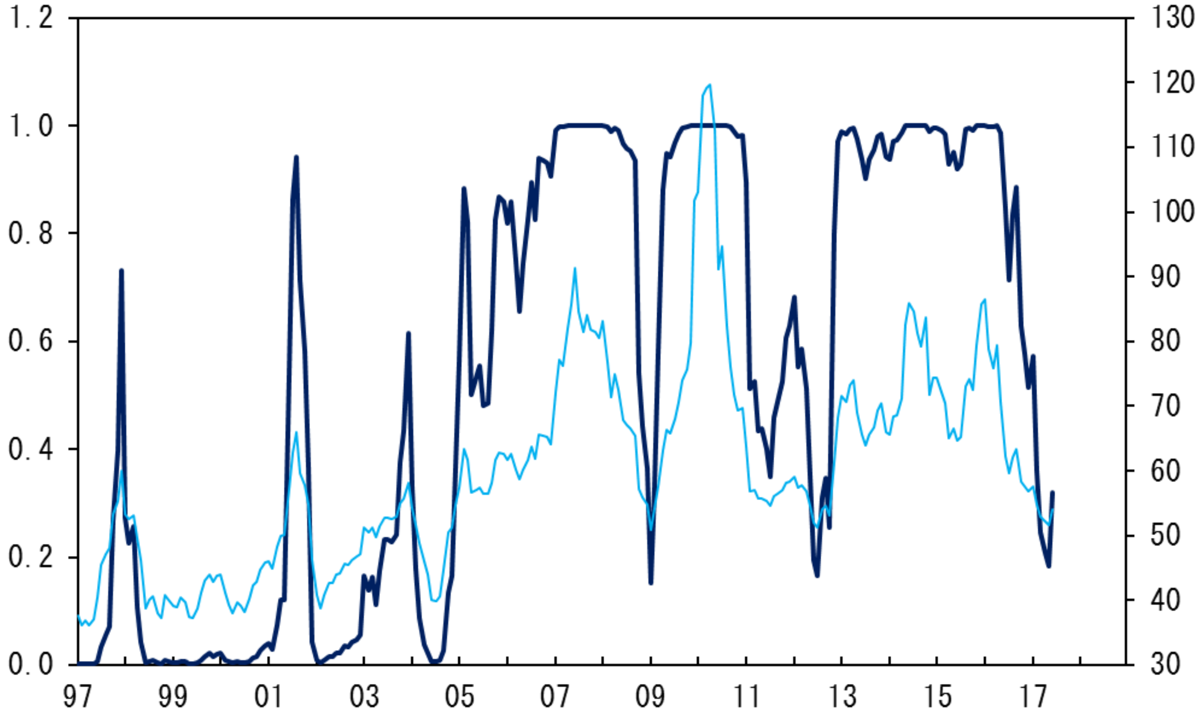

Figure 9: Probability of being in the high attention to climate change regime in the U.S.

Notes: The thin line represents six months backward moving averages of the CCN Index (right axis) and the solid line indicates the probability of being in the high attention to climate change regime (left axis) in the U.S.

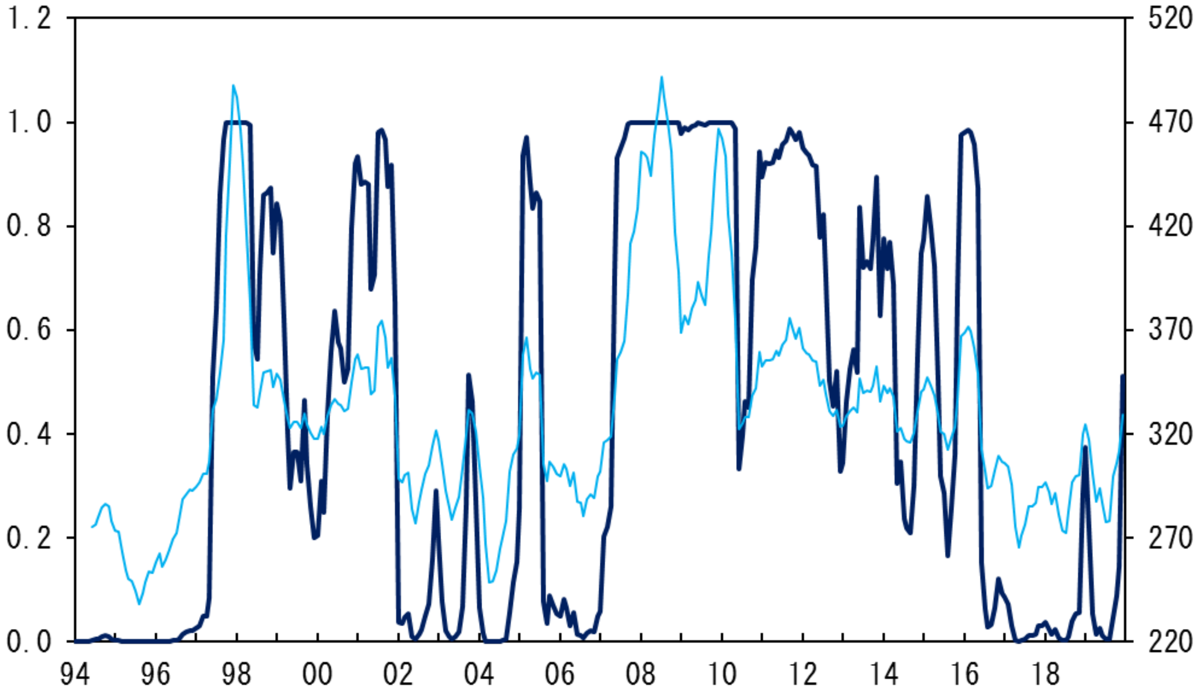

Figure 10: Probability of being in the high attention to climate change regime in the Japan.

Notes: The thin line represents six months backward moving averages of the CCN Index (right axis) and the solid line indicates the probability of being in the high attention to climate change regime (left axis) in Japan.

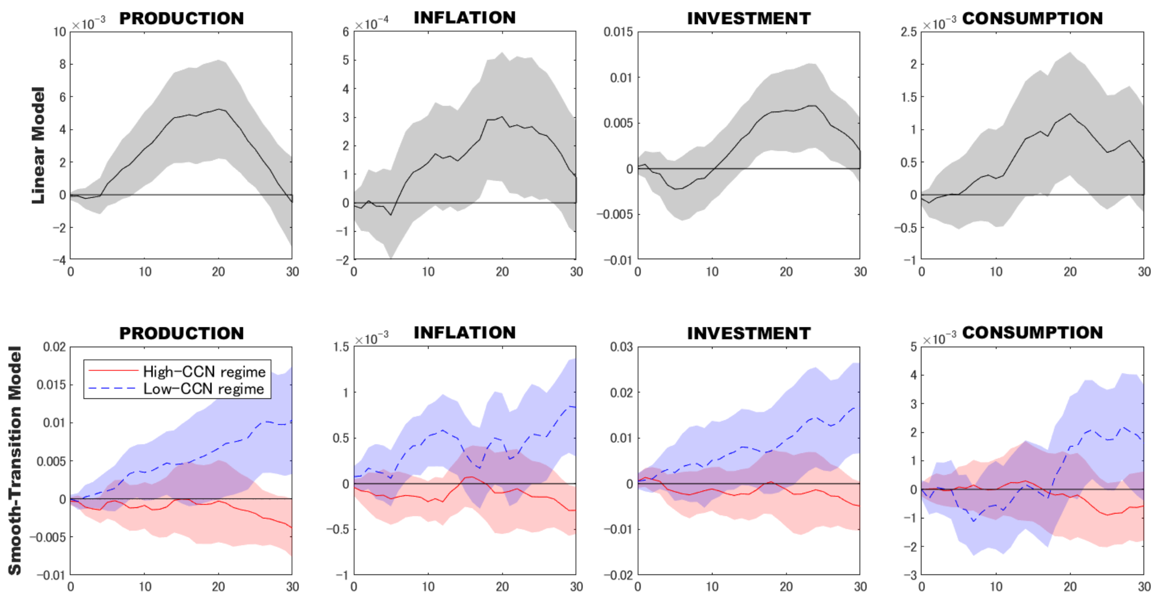

Figure 11: Responses to an expantionary monetary policy shock in the U.S.

Notes: This figure shows the impulse responses to an expantionary monetary policy shock in the U.S. The coefficients reflect the response to a 100 bps monetary policy shock. The shaded areas display 90% confidence bands based on Newey and West (1987) standard errors. INFLATION means PCE deflator. The upper panel shows the state independent responses (linear local projection model). In the lower panel, solid red (dashed blue) lines denote the responses during high attention to climate change (low attention to climate change).

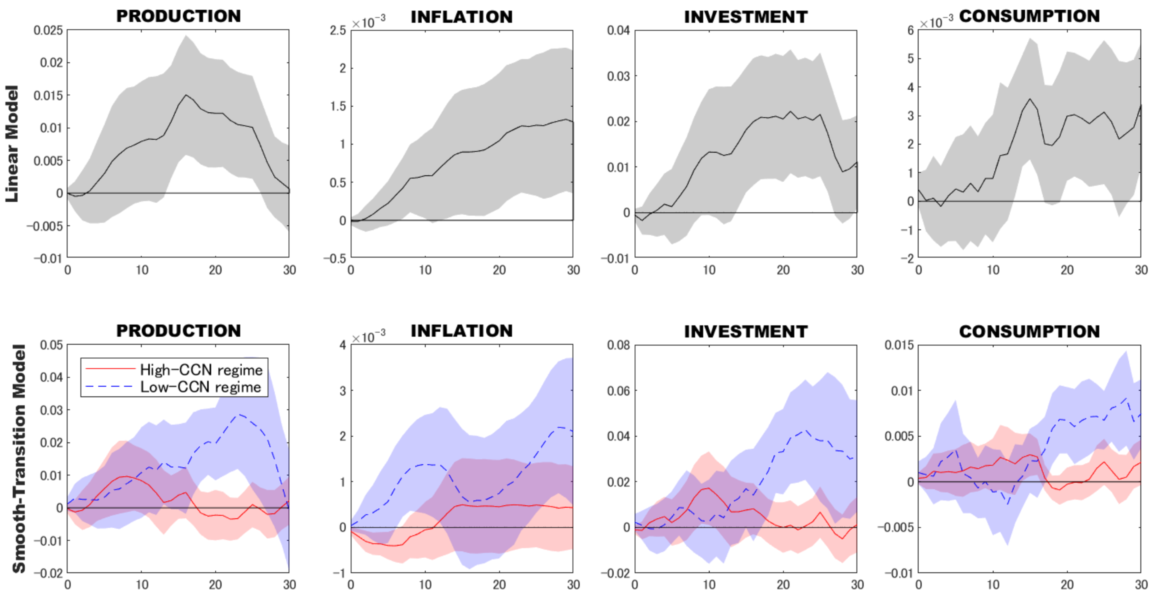

Figure 12: Responses to an expansionary monetary policy shock in Japan.

Notes: This figure shows the impulse responses to an expantionary monetary policy shock in Japan. The coefficients reflect the response to a 100 bps monetary policy shock. The shaded areas display 90% confidence bands based on Newey and West (1987) standard errors. INFLATION means consumer price index. The upper panel shows the state independent responses (linear local projection model). In the lower panel, solid red (dashed blue) lines denote the responses during high attention to climate change (low attention to climate change).

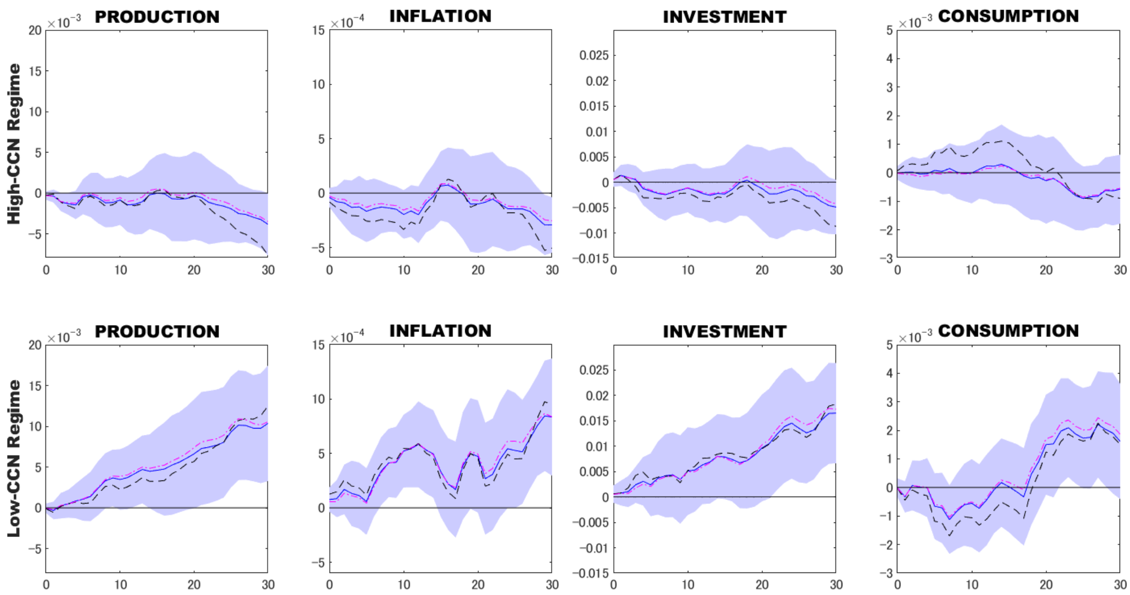

Figure 13: Robustness of the different value of θ in the U.S.

Notes: The upper panel shows the responses during high attention to climate change in the U.S. and the lower panel shows the responses during low attention to climate change. The solid line denotes the responses in $\theta = 5$(baseline), the dashed line denotes that in $\theta = 2$ and the dot-dash line denotes that in $\theta = 8$, respectively. The shaded areas display 90% confidence bands based on Newey and West (1987) standard errors around the baseline responses.

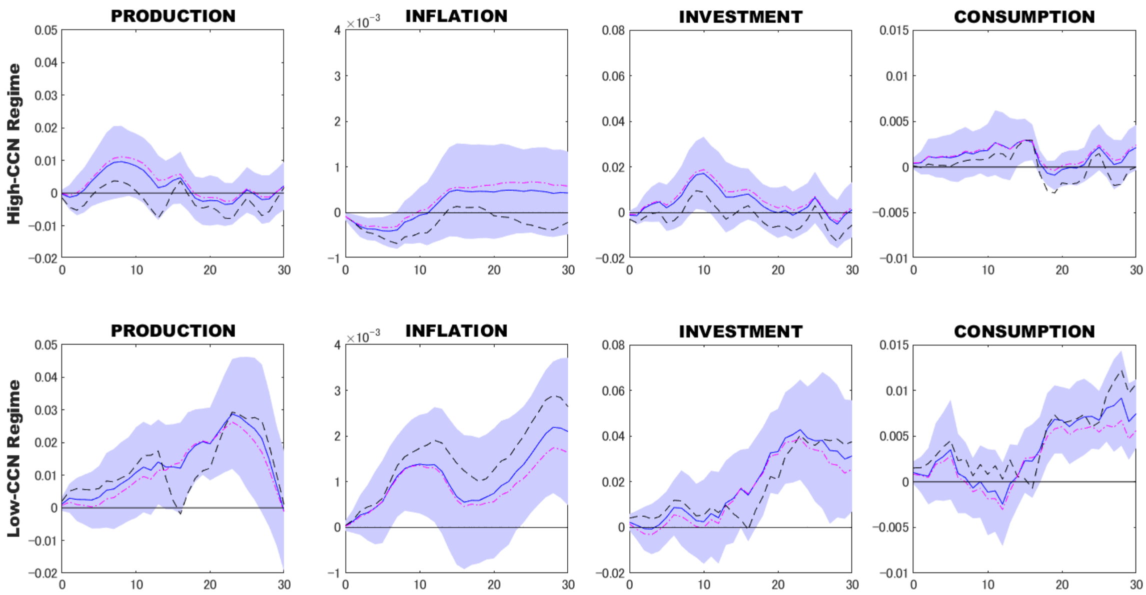

Figure 14: Robustness of the different value of θ in Japan.

Notes: The upper panel shows the responses during high attention to climate change in Japan and the lower panel shows the responses during low attention to climate change. The solid line denotes the responses in $\theta = 5$(baseline), the dashed line denotes that in $\theta = 2$ and the dot-dash line denotes that in $\theta = 8$, respectively. The shaded areas display 90% confidence bands based on Newey and West (1987) standard errors around the baseline responses.

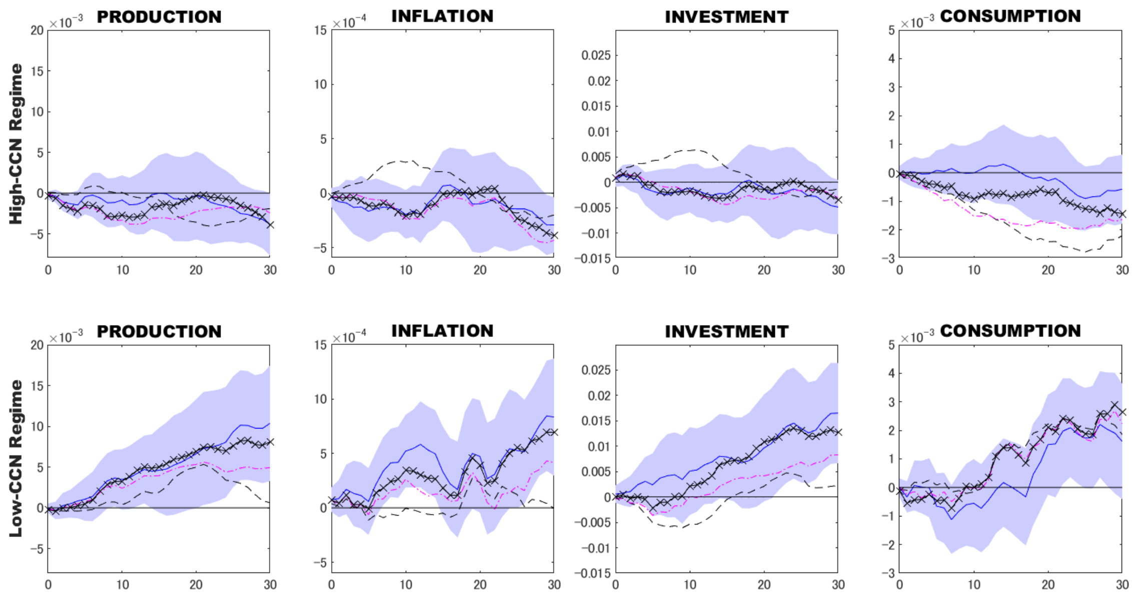

Figure 15: Robustness of the different lag of control variables in the U.S.

Notes: The upper panel shows the responses during high attention to climate change in the U.S. and the lower panel shows the responses during low attention to climate change. The solid line denotes the responses when the lag length is twelve (baseline), the dashed line denotes that when the lag length is three, the dot-dash line denotes that when the lag length is six and x denotes that when the lag length is nine, respectively. The shaded areas display 90% confidence bands based on Newey and West (1987) standard errors around the baseline responses.

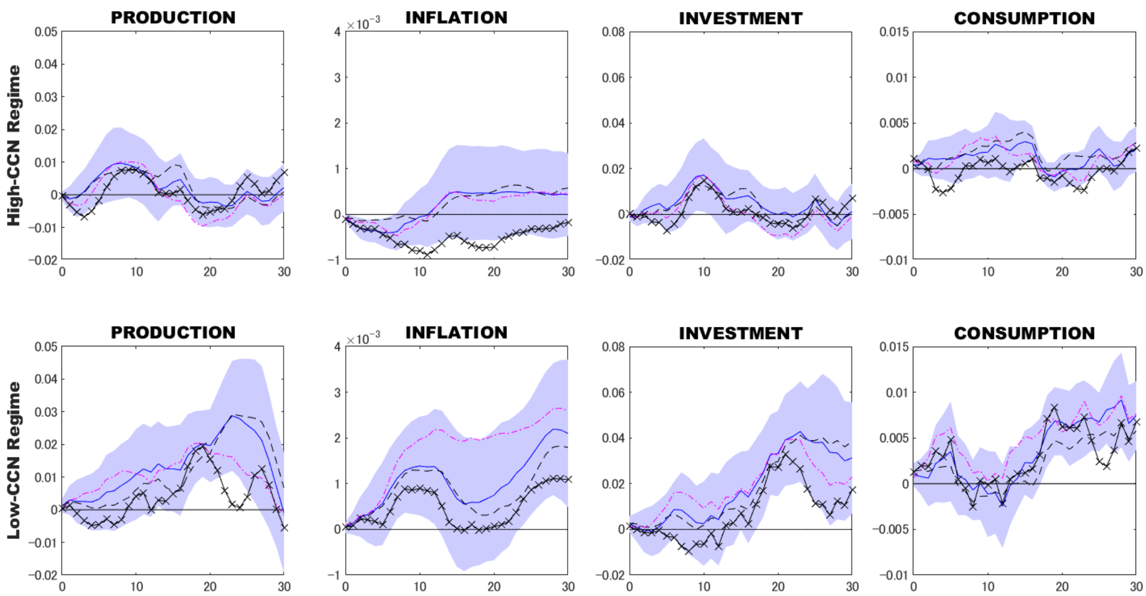

Figure 16: Robustness of the different lag of control variables in Japan.

Notes: The upper panel shows the responses during high attention to climate change in Japan. and the lower panel shows the responses during low attention to climate change. The solid line denotes the responses when the lag length is seven (baseline), the dashed line denotes that when the lag length is three, the dot-dash line denotes that when the lag length is nine and x denotes that when the lag length is twelve, respectively. The shaded areas display 90% confidence bands based on Newey and West (1987) standard errors around the baseline responses.

A Source of Japanese Climate Change Vocabulary

To create the Climate Change Vocabulary (CCV) in Japan, we collect Japanese climate change white papers issued from the ministry of the environment from 1997 to 2021. We extract the chapter on climate change from these white papers as shown below.

Table 3: List of climate change white papers

Year	Part	Chapter(Section)
1997	1	1(1,2,3)
1998	1	0(1), 3(1), 4(1)
1999	1	4(1)
2000	1	0(1)
2001	1	2(2)
2001	3	1(1)
2002	2	1(1)
2002	3	1(1)
2003	2	1(1)
2004	2	1(1,3), 7(3)
2004	3	1(2)
2005	1	1, 2, 3
2005	2	1(1,3), 7(3)
2005	3	1(2)
2006	2	1(1,3), 7(3)
2006	3	1(2)
2007	1	1, 2(3), 3(1,2,3,4,5)
2007	3	1(2), 7(8)
2007	4	1(1)
2008	1	1(1,2,3)
2008	2	1(2), 7(8)
2008	3	1(1)
2009	1	3(1,2,3)
2009	2	1(1,2,3), 6(8)
2009	3	1(1,2)
2010	1	2(1,2,3,4), 5(1,2,3,4)
2010	2	1(1,2,3), 6(8)
2010	3	1(1,2)
2011	1	4(3)
2011	2	1(1,2,3), 6(8)

Year	Part	Chapter (Section)
2011	3	1(1,2)
2012	1	4(1,2)
2012	2	1(1,2,3), 6(8)
2012	3	1(1,2)
2013	1	2(3)
2013	2	1(1,2,3), 6(2)
2013	3	1(1,2)
2014	1	1(1), 3(2,3,4)
2014	2	1(1,2,3), 6(2)
2014	3	1(1,2)
2015	2	1(1,2,3), 6(2)
2015	3	1(1,2)
2016	1	1(1,2)
2016	2	1(1,2,3), 6(2)
2016	3	1(1,2)
2017	1	2(1,2,3)
2017	2	1(1,2,3), 6(2)
2017	3	1(1,2)
2018	1	1(1,2)
2018	2	1(1,2,3), 6(2)
2018	3	1(1,2)
2019	1	2(1,2,3,4,5,6,7)
2019	2	1(1,2), 6(2)
2019	3	1(1,2)
2020	1	1(1,2,4), 2(1,2), 3(1,2)
2020	2	1(1,2), 6(2)
2020	3	1(1,2)
2021	1	1(2,4), 2(1)
2021	2	1(1,2), 6(2)
2021	3	1(1,2)

B Japanese CCN index using another source

We use another major newspaper in Japan, Nikkei Shinbun, to construct CCN index.

Appendix Figure 17 illustrates the developments of CCN index based on Nikkei Shinbun which is also one of major newspapers in Japan. As shown in the figure, our baseline CCN index based on Maichi shinbun is almost consistent with Nikkei-based CCN index. Also, the correlation between the two indices is 0.72. The correlation between the two CCN indices become 0.79, when they are converted to six-months backward moving average. The high correlation between two indices indicates that our CCN index is robust in terms of the data source[14].

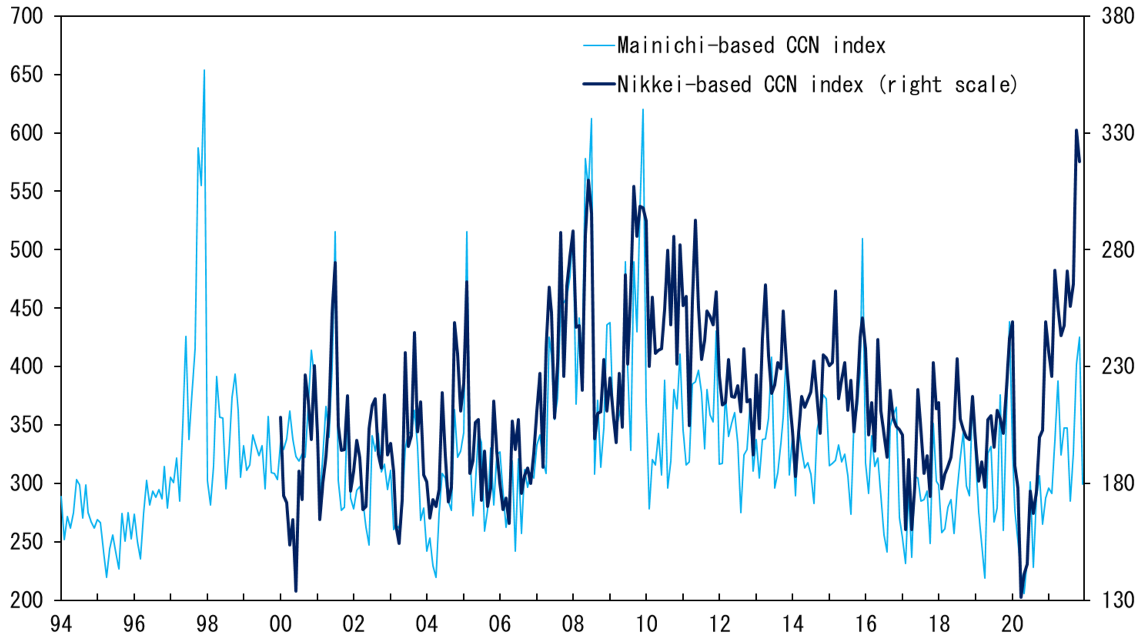

Figure 17: Japanese CCN index from Nikkei Shinbun

Notes: Each lines indicate six months backward moving averages.

[14]There are some differences in the developments of both indices. In particular, these indices are different in 2000, 2001, and after 2021, which suggests that newspapers may have different decision-making for how much they report on climate change.