IMES DISCUSSION PAPER SERIES

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Discussion Paper No. 2024-E-3

IMES

INSTITUTE FOR MONETARY AND ECONOMIC STUDIES

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JAPAN

IMES Discussion Paper Series 2024-E-3
April 2024

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Abstract

We construct a Climate Change News (CCN) index which measures attention to climate change risk for Japan, based on text information from newspaper articles. We compare our index 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 the correlation between the CCN indexes of the U.S. and Japan is much higher than the correlation between the CCN index and other uncertainty measures in either of those countries. We also find that shocks to the CCN indexes have significantly negative effects on economic sentiment, but have ambiguous effects on industrial production. This contrasts with the fact that, for both the U.S. and Japan, other uncertainty shocks 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 depends on the degree of attention to climate change risks.

Keywords: Climate Change; Text Analysis; Monetary Policy; Nonlinear Local Projection

JEL classification: E32, E52, Q54

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The authors would like to thank Jouchi Nakajima, Etsuro Shioji, Markus Heckel, Ulrich Volz, participants of the CEBRA Annual Meeting 2022, the 2022 JEA Autumn Meeting, the CMStatistics 2023, Sixth Annual Conference of the Japan Economy Network 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.

1 Introduction

Climate change is at the forefront of academic and policy debates. A growing body of literature has explored the negative impacts of climate change on the real economy, such as rising temperatures or sea levels and the increasing frequency of extreme weather events (Burke et al. (2015), Colacito et al. (2019), and Kim et al. (2022)). Additionally, climate change negatively affects financial markets through the damage to asset values associated with disasters (Ortega and Taṣpınar (2018), Alok et al. (2020), and Addoum et al. (2023)). Recently, the impact of climate change uncertainty and risk on financial markets has been discussed by Engle et al. (2020), Krueger et al. (2020), and Bua et al. (2022). They point out that climate change is affecting financial markets as investors begin to hedge against growing climate change-related risks. However, few empirical studies have examined the impact of climate change uncertainty and risk on the real economy.

Recent studies, pioneered by Bloom (2009), have found that various kinds of uncertainty have significant impacts on the real economy.[1] Some studies argue that increases in uncertainty related to economic policies (i.e., Economic Policy Uncertainty [EPU]) negatively affect the real economy (Baker et al. (2016), Caldara et al. (2020), and Husted et al. (2020)). Jurado et al. (2015), Scotti (2016), and Redl (2020) show that macroeconomic uncertainty (MU) has a detrimental effect on the real economy. Moreover, 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 of the impact of climate change uncertainty and risk on the real economy.

This study aims to fill these gaps in the literature. We examine how increasing uncertainties and concerns related to climate change affect the real economy. To this end, we follow Engle et al. (2020) and construct a climate change news (CCN) index that measures attention to climate change risks in Japan based on text information from newspaper articles. Engle et al. (2020) extract a climate news series using textual analysis based on The Wall Street Journal and build an index of attention to climate change for the U.S. (WSJ-CCN index). We apply this method to Japan and measure the extent to which attention is paid to climate change risks. Based on these indexes, we statistically investigate the link between climate change uncertainty and risk and the real economy.

[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."

This study's main contributions are twofold. First, we investigate the statistical properties of the CCN indexes. Focusing on the U.S. and Japan, we compare the indexes with three uncertainty-related indexes that are extensively used in the literature on uncertainty: EPU, MU, and VI.[2] Second, we examine the impact of changes in the CCN indexes on the real economy, focusing on economic sentiment and industrial production. Some theoretical studies focus on the expectation channel through which expectations about climate change impact the real economy (e.g., Dietrich et al. (2023) and European Central Bank (2021)). The intuition is straightforward. An increase in the probability of disasters related to climate change is bad news for people; thus, it depresses current economic activity. We empirically test the theoretical implications of this channel.

Furthermore, as an application of the CCN indexes, we examine how 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 the introduction of smooth regime switching between regimes with high and low attention to climate change risks. In this model, the transmission mechanism of monetary policy shocks can change depending on the level of attention to climate change risks. Hence, we estimate the regime-dependent impact of monetary policy shocks.

The main findings of this study are as follows:

- The correlation between the CCN indexes of the U.S. and Japan is much higher than the correlation between the CCN index and other uncertainty measures in either of those countries.

- Shocks to the CCN indexes have significantly negative effects on economic sentiment. However, they have ambiguous effects on industrial production. More specifically, shocks to the WSJ-CCN index have no significant impact on industrial production for the U.S., while the response of industrial production to the CCN shock is significantly negative for Japan. This contrasts with the fact that, for both the U.S. and Japan, other uncertainty shocks have negative effects on both economic sentiment and industrial production.

- The transmission of monetary policy weakens as climate change risks increase. In

[2] It should be noted that the CCN index may be better considered as a measure of public attention to climate change risk rather than a direct measure of climate change risk, such as the probability of natural disasters. In this respect, the CCN index differs from the other uncertainty measures we compare it with.

other words, responses of economic activity and inflation become significantly weaker as climate change risks increase for both the U.S. and Japan.

This study is closely connected to four strands of the literature. First, many empirical studies have found that climate change affects economies. Burke et al. (2015) use panel data for 166 countries and show that a nonlinear relationship exists 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 empirical studies that examine how climate variables such as temperature, precipitation, and windstorms influence economic outcomes. This study contributes to the literature by examining the impact of climate change uncertainty and risk on the real economy.

Second, this study contributes to the literature on the impact of uncertainty on the real economy. Several studies have focused on Economic Policy Uncertainty (Baker et al. (2016), Caldara et al. (2020), and Husted et al. (2020)), macroeconomic uncertainty (Jurado et al. (2015), Scotti (2016), and Redl (2020)), and financial market volatility (Bloom (2009), Bonciani and Ricci (2020), and Ludvigson et al. (2021)). What sets this study apart from the literature is its examination of the impact of uncertainty or risk associated with climate change on the real economy.

Third, several studies have focused 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.[3] 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 a disaster, an increase in its probability decreases consumption and wages. They argue that this effect can be interpreted as a shift in the agents' degree of patience.

Expectations about natural disasters due to climate change are examples of rare-disaster expectations. Dietrich et al. (2023) conduct a survey in the U.S. to measure expectations about the economic impact of climate change. They find that respondents change their expectations owing to various factors, including media consumption, and tend to assign high probabilities to natural disasters. They also calibrate a New Keynesian model for rare

[3]They define a "rare-disaster" as an infrequent and large macroeconomic shock, including not only natural disasters but also wars or financial crises.

disasters and show that disaster expectations could lower the natural rate of interest. We empirically confirm this mechanism and quantify how it affects monetary policy transmission.

Fourth, this study contributes to the growing empirical literature on the state-dependent effects of fiscal and monetary policy shocks. 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) employ a similar local projection method to study the efficacy of monetary policy shocks during booms and recessions. They find that monetary policy is less powerful during recessions. Weise (1999) estimates a smooth transition VAR model and demonstrated that money supply shocks have a greater impact on output but a lesser impact on inflation when the growth rate of output is lower. Miyao and Okimoto (2020) examine the effects of unconventional monetary policy in Japan using a smooth transition VAR model, with the level of unconventional assets held by the Bank of Japan as a transition variable. Their findings suggest that the effects of monetary policy become more pronounced following the introduction of quantitative and qualitative monetary easing. Aastveit et al. (2017), Castelnuovo and Pellegrino (2018) and Pellegrino (2021) empirically explore if economic uncertainty alters the effectiveness of monetary policy. They employ non-linear structural VAR models and show that monetary policy shocks are less powerful when uncertainty is high. Aastveit et al. (2017) argue that the results are consistent with the hypothesis that agents gather more information and postpone decisions under high uncertainty, and that this "wait-and-see" behavior makes them less responsive to changes in the economic environment such as interest rates. Furthermore, 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 under high disagreement, whereas it leads to a significant decline in these variables under low disagreement. Based on these studies, we focus on climate change risk.

The remainder of this paper is organized as follows. Section 2 presents a method for measuring attention to climate change risks. In Section 3, we present a statistical analysis of the CCN indexes. As an application of the CCN indexes, Section 4 investigates whether monetary policy effectiveness depends on the degree of attention to climate change risks.

Finally, Section 5 concludes the paper with suggestions for future research.

2 Climate Change News Index

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

2.1 WSJ-CCN Index of Engle et al. (2020)

Engle et al. (2020) propose an index (WSJ-CCN index) measuring innovations in news on climate risk. They construct the index to extract news on climate change using textual analysis from The Wall Street Journal (WSJ).

The construction of the WSJ-CCN index follows three steps. First, they make a corpus of climate change-related risks that appear in official reports. Official white papers on climate change include those of the Intergovernmental Panel on Climate Change, the Environmental Protection Agency, and the U.S. Global Change Research Program. Based on these white papers, they construct a "Climate Change Vocabulary (CCV)." They create a list of unique terms and define the CCV as the frequency at which each term is found in the corpus of all white papers. 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 fossil fuel prices.

Second, they create term frequency–inverse document frequency scores for the CCV, called $tf\text{-}idf$ scores. They also generate a daily count of terms used in the WSJ. They count the term separately for every issue of the WSJ. These term counts are then converted into $tf\text{-}idf$ scores. The term "tf" refers to term frequency, which represents the number of times a term appears in a specific document. When a term j is not commonly found in a document i, it does not accurately represent the document; therefore, $tf_{i,j}$ is small. The term "idf" refers to inverse document frequency, which is calculated as the logarithm of one divided by the proportion of documents containing a specific word. $tf\text{-}idf_{i,j}$ is derived by multiplying $tf_{i,j}$ and idf_j for every term j and document i. Consequently, $tf\text{-}idf_{i,j}$ identifies the most important term in a document by assessing its frequency within that document and its rarity across all documents.

Finally, using the $tf\text{-}idf$ scores of the CCV and daily WSJ editions, they create a daily climate change index based on the "cosine similarity" between the two. An index value of one is assigned to days when the WSJ and CCV use identical terms in the same ratio. However, if the WSJ does not use words from the CCV, the index value is zero. The WSJ-CCN index provides an approximate representation of the amount of climate change coverage in the WSJ on a daily basis, as determined by the underlying texts in the CCV. The index is multiplied by 10,000 to make the innovation magnitudes easier to understand.

Figure 1 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 occur, such as the Copenhagen Accord of December 2009 and the publication of the Third National Climate Assessment in May 2014. It also indicates that the climate news coverage intensity in the U.S. has steadily increased and remained high since the mid-2000s. We use this WSJ-CCN index to capture attention to climate change risks in the U.S.[4]

2.2 CCN Index for Japan

We apply the approach of Engle et al. (2020) to extract the CCN index for Japan. We use textual news coverage in The Mainichi Shimbun newspaper, one of the major newspapers in Japan, from 1994 onward, covering a wide range of Japanese and world news.[5]

We also collect data from 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. These white papers cover various topics, including industrial waste and biodiversity. We extract the chapters on climate change. Appendix Table A.1 presents a

[4]Engle et al. (2020) note that this index is constructed under the assumption that CCN is bad news or related to risks. To justify this premise, they construct another index designed to focus on negative news about climate change. They confirm that both indexes spike around salient climate events and indicate a high correlation across these measures. In conclusion, they argue that both indexes capture common elements of climate change risks.

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

full list of these authoritative texts. The collected documents consist of statements about climate change, such as an increase in natural disasters, and actions to mitigate climate change.

We then follow the same steps as in Engle et al. (2020) to construct our CCV for Japan. Figure 2 illustrates the CCV for Japan in the form of a word cloud. The font sizes of the terms are proportional to their frequency. The CCV is mainly composed of words such as "environment" and "emissions," which is consistent with Engle et al. (2020). These words imply a physical risk, such as an increase in extreme weather events. Furthermore, the CCV includes other aspects of climate risk, such as transition risk. Terms such as "countermeasure," "reduction," and "implementation" are representative of the transition risk topic.[6]

Following the same steps as in Engle et al. (2020), we obtain tf-idf scores for the CCV and construct our daily index of attention to CCN based on the cosine similarity between the tf-idf vector for the CCV and for each daily issue of The Mainichi Shimbun. Figure 3 presents the CCN index for Japan from January 1994 to December 2021. The index increased steeply when global climate treaties and major global conferences were implemented to prevent climate change. As the previous subsection shows, this is consistent with the indexes observed for the U.S.

As a robustness check, we use another major Japanese newspaper, The Nikkei Shimbun, to construct a CCN index for Japan. Appendix Figure B.1 illustrates the development of the CCN index from the Nikkei. The figure indicates that the CCN indexes from both The Mainichi Shimbun and The Nikkei Shimbun increased during the same period. Furthermore, the correlation between the two CCN indexes is 0.72; therefore, our CCN index for Japan is robust in terms of the data source.

3 Statistical Analysis on Climate Change News Index

To understand the statistical features of the CCN indexes, we investigate how the CCN indexes are correlated with three other measures of economic uncertainty. We also evaluate the impact of changes in the CCN index on economic sentiment and industrial production,

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

as well as that in the three uncertainty measures.

3.1 Three Alternative Measures on Economic Uncertainty

We compare the CCN indexes with three measures that are commonly used in empirical studies on uncertainty in macroeconomics. The first measure is the EPU indexes for the U.S. and Japan. The EPU index for the U.S. is calculated by Baker et al. (2016), and Arbatli et al. (2022) calculate 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] EPU is computed as the ratio of the number of articles that include at least one word listed in all three categories, namely, "economy," "policies," 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, debt ceiling disputes, wars, and financial crises.

The second is the MU index, which measures uncertainty by computing the common factor of the time-varying volatility of forecast errors from a large number of economic time series. This implies that it captures the uncertainties caused by various macroeconomic factors simply and comprehensively. For example, the MU index for Japan rose sharply during economic downturns, such as the Global Financial Crisis, and during other events, such as 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 calculated by Shinohara et al. (2020).

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

We select the three uncertainty-related indexes discussed above because there is extensive empirical literature on the statistical properties of these measures; thus, their properties are well understood. Therefore, by comparing the CCN indexes with these three

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

measures, we can improve our understanding of how different the climate change-related issues are from economic uncertainty.

3.2 Correlations among Uncertainty Indexes

First, we compute the correlations among the indexes based on monthly measures.[8] Table 1 summarizes the correlation coefficients for each pair. Panel (a) presents the results for the U.S., and three findings are worth noting. First, the first column of Panel (a) shows that the correlation between the CCN index and the other economic uncertainty measures is significantly positive or not statistically significant. Specifically, the correlation of the WSJ-CCN index with EPU is 0.06, and its correlations with MU and VI are 0.18 and -0.07, respectively.

Second, the correlation between the CCN for the U.S. (WSJ-CCN) and the CCN index for Japan is 0.45. Therefore, the WSJ-CCN index is more correlated with the CCN index for Japan than with other MU measures for the U.S., which suggests that concerns about climate change are driven by common factors in the U.S. and Japan, such as salient global climate events or global discussion trends on climate change risks.

Third, the correlations among other economic uncertainty measures are significantly positive and higher than those of other economic uncertainty measures with the WSJ-CCN index, except for the correlation between EPU and MU. The correlation coefficient between EPU and MU is 0.27, which is comparable to the correlation between the CCN index and other uncertainties. However, the correlation between EPU and the volatility index is 0.45, and that between MU and the volatility index is 0.58. Both are higher than the correlation of the CCN index with other uncertainty measures. This indicates that the development of attention toward climate change risks differs from other economic uncertainty measures.

Examining the results for Japan (Panel [b]), we find the same implications as for the U.S. The CCN index for Japan exhibits the highest correlation with the CCN index for the U.S. (WSJ-CCN). On the other hand, the correlations between the CCN index and other economic uncertainty measures are all significantly positive.

To determine whether there is a prior lagged relationship between CCN for the U.S. (WSJ-CCN) and CCN for Japan, we calculate their cross correlations. We find that there is no prior lagged relationship between the attention to climate change risks for the U.S.

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

and Japan. Figure 4 shows the results of calculating the cross correlations between them. Notably, the correlation coefficients are largest when there is no time lag, and the cross correlations are symmetric around lag zero. Therefore, the CCN indexes for both countries move similarly in response to climate change-related events.[9]

The results discussed above suggest that climate change concerns are driven by common factors in the U.S. and Japan, such as salient global climate events and global trends in discussions on climate change risks. Moreover, the development of attention toward climate change risks differs from other economic uncertainties.

3.3 Uncertainty, Sentiment and Economic Activity

We evaluate the impact of the CCN indexes on the real economy. Specifically, we focus on economic sentiment and industrial production. Economic sentiment in the U.S. is estimated by Shapiro et al. (2022), and UTEcon 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) note that news sentiment has a predictive power regarding the movements of survey-based consumer sentiment; its development can affect real variables such as consumption and output.

3.3.1 Correlations with Sentiment and Industrial Production

Panel (a) of Table 2 shows the correlation coefficients for the U.S. What is worth noting is that, as with other economic uncertainty measures, the correlation between the CCN index and economic sentiment or industrial production is significantly negative. The correlation coefficients between news sentiment and CCN, EPU, MU, and VI are -0.17, -0.61, -0.50, and -0.53, respectively. Furthermore, the correlation coefficients of industrial production with CCN, EPU, MU, and VI are -0.25, -0.32, -0.74, and -0.34, respectively.

Panel (b) of Table 2 shows that the finding discussed above is also true for Japan. Therefore, it can be concluded that the CCN index, as well as other economic uncertainty measures, are negatively correlated with economic sentiment and industrial production, at least in simple correlations.

[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 other countries, such as those in Europe, could influence the attention to climate change risks in the U.S. and Japan.

[10]See Goshima et al. (2022) and the UTEcon website for the details.

To wrap up, several descriptive statistics show that the relationship between the CCN indexes and the real economy is negative. We formally examine this relationship in the following section.

3.3.2 Impulse Responses of Sentiment and Industrial Production to Uncertainty Shocks

Here, we investigate how shocks to the CCN index and other uncertainty measures are propagated to news sentiment and the real economy in a structural vector autoregressive (VAR) framework using data from the U.S. and Japan. To identify uncertainty shocks, we follow Bachmann et al. (2013) and Baker et al. (2016), among others, and employ the recursive identification scheme with an uncertainty measure being ordered first in the VAR(p) model given by

$$X_t = \sum_{k=1}^{p} B_k X_{t-k} + C\varepsilon_t, \tag{1}$$

where X_t is an $n \times 1$ vector of variables, B_k's and C are $n \times n$ coefficient matrices, ε_t is an $n \times 1$ vector of structural shocks with $E(\varepsilon_t) = 0$ and $E(\varepsilon_t \varepsilon_t')$ is a diagonal matrix. The C matrix is a nonsingular matrix with all the elements in the first row being zero except for the first one. The uncertainty shock corresponds to the first element of ε_t. In other words, an uncertainty measure is assumed to respond contemporaneously only to the uncertainty shock but not to other structural shocks. Since we are only interested in the impulse responses to the uncertainty shock, we do not identify the remaining structural shocks.

The first specification we consider is a simple bivariate VAR model with $n = 2$ and $X_t = [un_t, y_t]'$, where un_t is a measure of uncertainty and y_t is either industrial production or economic sentiment. We refer to this bivariate specification as "VAR-2." The second specification we consider is an eight-variable VAR model. In particular, we set $n = 8$ and let $X_t = [un_t, y_t, x_{1t}, ..., x_{6t}]'$ where un_t and y_t are the same as the VAR-2 specification. The additional six variables $x_{1t}, ..., x_{6t}$ are: (i) log of the stock prices; (ii) short-term interest rate; (iii) log of nominal wages; (iv) log of the consumer price index; (v) hours worked, (vi) log of employment.[11] We refer to this second specification as "VAR-8." For the stock price

[11] Note that Bloom (2009) used the stock volatility index as a proxy for uncertainty and estimated the eight-variable VAR model by placing the stock price first and the stock volatility index second. We also employ such an alternative identification scheme but results remain unchanged.

variable, we use the S&P 500 for the U.S. and the TOPIX index for Japan. For the short-term interest rate, we use the Federal Funds Rate for the U.S. and the Uncollateralized Overnight Call Rate for Japan.

Figure 5 lays out the responses of news sentiment or industrial production to a one standard deviation shock to the CCN index or other uncertainty measures for the U.S. Based on the BIC, the lag length p was set to two in the U.S. for both specifications. As is shown in the figures, news sentiment decreases significantly in response to shocks to uncertainty measures and the CCN index, except for the case of VAR-8 with the CCN index. On the other hand, for the industrial production, the shocks to uncertainty measures have significantly negative impacts on industrial production, consistent with the findings of Bloom (2009), while the shocks to the CCN index have no significant impact on industrial production in either the VAR-2 and VAR-8 specifications.

Figure 6 shows the results for Japan. Based on the BIC, the lag length p was set to two for VAR-2 concerning economic sentiment and one for other specifications in Japan. For both specifications, the results suggest that news sentiment is significantly reduced by an uncertainty shock in the CCN index and other uncertainty measures. Shocks in the three uncertainty measures also have significant negative impacts on industrial production. On the other hand, the response of industrial production to shocks in the CCN index is somewhat ambiguous. In the U.S., shocks to the CCN index have no significant effect on industrial production regardless of the VAR specification, while in Japan, the CCN shocks significantly reduce industrial production in the VAR-8 specification. Therefore, the results for both the U.S. and Japan show that there is a clear difference between the CCN index and other uncertainty indexes in terms of their impact on industrial production, but not on economic sentiment. These results imply that, while attention to climate change risks can exacerbate economic sentiment, it does not necessarily lead to an immediate stalling of economic activity.[12]

To check the robustness of our findings based on the VAR model, we also estimate the impulse responses to uncertainty shocks using the local projection method developed by Jordà (2005). Let y_t be the variables of interest, namely, economic sentiment or industrial production. The impulse response β_h of y_t to an uncertainty shock at horizon $h(\geq 0)$ can

[12]This contrast becomes more apparent in the local projection methods described below.

be obtained by running a regression of the form:

$$y_{t+h} = \alpha_h + \beta_h un_t + \gamma_h' \boldsymbol{x}_t + u_{t+h} \tag{2}$$

where un_t is one of the uncertainty measures, including the CCN index, $\boldsymbol{x}_t$ is a vector of control variables and u_{t+h} is the regression error term. As in the VAR analysis, we consider two specifications. The first one is a bivariate specification where we set $\boldsymbol{x}_t = [un_{t-1}, y_{t-1}, ..., un_{t-p+1}, y_{t-p+1}]'$. The second one is an eight-variable specification where we set $\boldsymbol{x}_t = [un_{t-1}, y_{t-1}, x_{1,t-1}, ..., x_{6,t-1}, ..., un_{t-p+1}, y_{t-p+1}, x_{1,t-p+1}, ..., x_{6,t-p+1}]'$. In what follows, we denote the first specification as “LP-2” and the second specification as “LP-8.”

The estimation results are shown in Figure 7 for the U.S. and Figure 8 for Japan. The impulse responses from the local projection are consistent with the VAR results with respect to uncertainty measures. An increase in economic policy uncertainty, macroeconomic uncertainty or stock market volatility reduces both sentiment and industrial production in the U.S. and Japan. In addition, for both the U.S. and Japan, the CCN index has significantly negative effects on economic sentiment. However, the impulse responses of industrial production to CCN shocks have different implications in the U.S. and Japan. Shocks to the CCN index have no significant impact on industrial production for the U.S. in the LP-2 specification, while the response of industrial production to the CCN shock is significantly negative regardless of the model for Japan. These results from both VAR models and local projections indicate that the effect of CCN shocks on industrial production is ambiguous and can be different between the U.S. and Japan.

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

4 Application of the CCN Indexes to Monetary Policy

This section presents our empirical approach to estimate how attention to climate change risks influences the transmission of monetary policy shocks. To quantify this, we apply the local projection method developed by Jordà (2005). Departing from Jordà (2005), our approach allows smooth regime switches, following Auerbach and Gorodnichenko (2012) and Tenreyro and Thwaites (2016). In our estimation, the regimes are identified by focusing on climate change risks. Based on this model, the transmission mechanism of monetary policy shocks can potentially change depending on the extent of the attention to climate change risks. The following section describes our econometric model and data sources.

4.1 Local Projection with a Regime Shift

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

$$y_{t+h} = \tau_h t + (\alpha_h^H + \beta_h^H \epsilon_t + \gamma_h^H \boldsymbol{x}_t) F(z_t) + (\alpha_h^L + \beta_h^L \epsilon_t + \gamma_h^L \boldsymbol{x}_t)(1 - F(z_t)) + u_{t+h} \tag{3}$$

where $h(\geq 0)$ indicates the number of periods after a shock hits the economy and superscripts H and L on coefficients refer to the high (H) and low (L) attention regimes, respectively. A time trend is denoted as $\tau_h t$. We control for the regime-specific constants $\alpha_h^{H,L}$, regime-dependent effects of the monetary policy shock $\beta_h^{H,L}$, and a set of regime-specific coefficients $\gamma_h^{H,L}$. Control variables $\boldsymbol{x}_t$ includes industrial production, consumption, firms' capital investment, consumer prices, and corporate bond spreads. We use corporate bond spreads as a control variable because they could be a source of business cycle fluctuations (Gilchrist and Zakrajšek (2012)).[13] A measure of monetary policy shock is denoted as ϵ_t and u_{t+h} refers to the regression residual.

The regimes are identified using the transition variable z_t. For z_t, we use the six-month backward-moving average of the CCN index, reflecting the recent level of attention to climate change risks. For the smooth transition function $F(z_t)$, we use the logistic function

[13] Bu et al. (2021) add excess bond premiums to their VAR model for the same reason.

given by:

$$F(z_t) = \frac{\exp\left(\theta \dfrac{z_t - c}{\sigma_z}\right)}{1 + \exp\left(\theta \dfrac{z_t - c}{\sigma_z}\right)} \tag{4}$$

where c is the mean and σ_z is the standard deviation of z_t. The function increases in z_t. The parameter θ determines the curvature of $F(z_t)$, and hence, how strongly the probability reacts to changes in attention to climate change risks. Because of the difficulty in estimating θ with good precision, previous studies often used calibrated values (Auerbach and Gorodnichenko (2012), Tenreyro and Thwaites (2016), and Falck et al. (2021)). We follow the literature and set the value at $\theta = 5$. However, our results are robust to a wide range of values, as mentioned in Appendix C.

To estimate the impulse responses, we use local projections that provide a direct estimate of the response of the dependent variable h periods after shock ϵ_t, depending on whether the economy is in a high- or low-attention regime when the shock occurs. The estimation of Eq.(3) is repeated for each horizon h, and the set of $\beta_h^{H,L}$ reflects the impulse response function for y_t in period h.

By introducing $F(z_t)$, we allow for the possibility of two regimes with respect to attention to climate change risks, which are characterized by potentially different macroeconomic dynamics. The response of the endogenous variable, y_{t+h}, to a monetary policy shock ϵ_t depends on the probability of being in a high- or low-attention regime, $F(z_t)$. Hence, the effects of monetary policy shocks are potentially conditioned by the probability of being in a high- or low-attention regime.

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

We estimate econometric models for the U.S. and Japan separately. By comparing the estimation results in the U.S. with those in Japan, we can examine if the effects of monetary policy differs between the two countries.

In our benchmark specification, the control variables are twelve lags in the U.S. and seven lags in Japan, as determined by the Akaike information criterion. The results remain unchanged when the lag lengths of the control variables change, as mentioned in Appendix C.

4.2 Data

We use monthly data from the U.S. and Japan. As mentioned above, the data include industrial production, consumption, firms' capital investment, consumer prices, and corporate bond spreads. The estimation period covers October 1997 to December 2019 because of the availability of data for corporate bond spreads. We exclude 2020 because COVID-19 dramatically affected economies, which might distort our estimation.

The price index for the U.S. is the PCE deflator excluding food and energy, whereas we use the 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 investment. The consumption index is the PCE for the U.S. and the retail sales value for Japan. The indexes for industrial production, consumer prices, firms' capital investment, and consumption are three-month moving averages for smoothing. The corporate bond spreads are the ICE BofA US High Yield Index (option-adjusted spread) for the U.S. and BBB-rated corporate bond spreads for Japan. We take the logarithms of indexes other than corporate bond spreads.

Regarding monthly monetary shocks, we use exogenous monetary policy shocks, as in the literature. We follow Bu et al. (2021) for the U.S. and Kubota and Shintani (2022) for Japan. Both studies develop shock series that stably bridge the periods of conventional and unconventional monetary policies. These series are largely unpredictable from the available information on the economy and contain no significant central bank information effect. This allows for a cleaner inference of the transmission of an exogenous monetary policy shock.

4.3 Results

4.3.1 Identifying Periods of High and Low Attention to Climate Change Risks

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

Specifically, the probability of being in a low-attention regime is relatively high throughout the first half of the sample period in both the U.S. and Japan. However, the probability of being in a high-attention regime increased after the mid-2000s in both countries. This implies that more people have become concerned about climate change risks in recent years. Furthermore, unlike in the U.S., the probability of being in a high-attention regime was high between 1998 and 2002 in Japan. This is because Japan held the Kyoto Protocol meetings and more Japanese people were paying attention to climate change risks during that period.

4.3.2 The Regime-dependent Transmission of Monetary Policy Shocks

Figures 11 and 12 show the impulse responses of industrial production, consumer prices, firms' capital investment, and consumption to an expansionary 100 basis points monetary policy shock in the U.S. and Japan, respectively. The upper rows in Figures 11 and 12 show the results of the linear model estimated without assuming regime changes, implying that state-dependent effects are not considered. Meanwhile, the lower panels in both figures show the results of our regime-switching approach. The responses in regimes with high and low attention to climate change risks are presented. The red solid lines and blue dotted lines represent the impulse responses in the high- and low-attention regimes, respectively.

The upper panels in Figures 11 and 12 indicate that all variables significantly increase with an expansionary monetary policy shock. This finding is consistent with the implications of standard New Keynesian models and related empirical studies.

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

Second, the transmission of monetary policy becomes significantly weaker in a regime with high attention to climate change risks. Specifically, the responses to monetary policy shocks in a low-CCN regime (dashed blue lines) are almost the same as those of the linear model. Thus, all variables increase significantly in a low-CCN regime in response to expansionary monetary policy shocks. Figure 11 shows that, after twenty months, industrial production significantly increases by approximately one percentage points and the inflation rate also rises by approximately 0.1 percentage point in the U.S. Meanwhile, the responses of all variables to expansionary monetary policy shocks in a high-attention regime (solid red lines) are not significant, which implies that the transmission of monetary policy becomes weaker.[14]

This is also true for Japan. The lower panels in Figure 12 show the responses to an expansionary monetary policy shock in regimes with high and low levels of attention to climate change risks in Japan. The first column shows that the response of industrial production significantly increases by approximately three percentage points after twenty periods in the low-CCN regime. By contrast, the response is insignificant in the high-CCN regime. In the third and fourth columns, the responses of firms' capital investment and consumption in the low-CCN regime are statistically significant. However, the responses in the high-CCN regime are small and statistically insignificant.

The lower panels in Figures 11 and 12 also indicate that the responses of almost all variables are statistically different in regimes with high and low attention to climate change risks in both the U.S. and Japan.[15]

5 Conclusion

This study statistically investigates the impact of attention to climate change risks in the U.S. and Japan. We find that for both the U.S. and Japan, the CCN index has significantly negative effects on economic sentiment but has ambiguous effects on industrial production, which is inconsistent with the fact that other uncertainty measures have negative effects on both economic sentiment and industrial production.

We apply the CCN index to investigate how changes in attention to climate change risks alter the transmission of monetary policy. We find that monetary policy effectiveness

[14]Some empirical studies explore whether economic uncertainty alters monetary policy effectiveness (Aastveit et al. (2017), Castelnuovo and Pellegrino (2018), and Pellegrino (2021)). They employ nonlinear structural VAR models and show that monetary policy shocks are less powerful when uncertainty is high. Aastveit et al. (2017) argue 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.

[15]We present the robustness check in the Appendix C.

depends on the degree of attention to climate change risks.

One additional direction for future research is to construct a model to interpret our empirical findings and provide some policy analysis. For example, we can include a mechanism for the transmission of transition risk in addition to physical risk. This would allow us to consider more channels of climate change risks. Another possible approach is to apply a smooth-transition VAR. This would allow us to investigate how the transmission of structural shocks, such as demand and supply shocks, depends on the state of climate change risks.

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Table 1: Correlation coefficients between uncertainty measures

(a) US

	Climate Change News (CCN)	Economic Policy Uncertainty (EPU)	Macroeconomic Uncertainty (MU)	Stock Market Volatility (VI)
CCN	1.00 –			
EPU	0.06 (0.06)	1.00 –		
MU	0.18*** (0.06)	0.27*** (0.06)	1.00 –	
VI	-0.07 (0.06)	0.45*** (0.05)	0.58*** (0.06)	1.00 –
CCN(Japan)	0.45*** (0.05)			

(b) Japan

	Climate Change News (CCN)	Economic Policy Uncertainty (EPU)	Macroeconomic Uncertainty (MU)	Stock Market Volatility (VI)
CCN	1.00 –			
EPU	0.23*** (0.06)	1.00 –		
MU	0.30*** (0.06)	0.17*** (0.06)	1.00 –	
VI	0.19*** (0.06)	0.53*** (0.05)	0.55*** (0.05)	1.00 –
CCN(US)	0.45*** (0.05)			

Notes: Correlation coefficients with standard errors in parentheses. *** 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) US

	Climate Change News (CCN)	Economic Policy Uncertainty (EPU)	Macroeconomic Uncertainty (MU)	Stock Market Volatility (VI)
News Sentiment	-0.17*** (0.06)	-0.61*** (0.05)	-0.50*** (0.05)	-0.53*** (0.05)
Industrial Production	-0.25** (0.06)	-0.32*** (0.06)	-0.74*** (0.04)	-0.34*** (0.06)

(b) Japan

	Climate Change News (CCN)	Economic Policy Uncertainty (EPU)	Macroeconomic Uncertainty (MU)	Stock Market Volatility (VI)
News Sentiment	-0.20*** (0.06)	-0.59*** (0.05)	-0.34*** (0.06)	-0.63*** (0.05)
Industrial Production	-0.17*** (0.06)	-0.28*** (0.06)	-0.49*** (0.05)	-0.41*** (0.05)

Notes: Correlation coefficients with standard errors in parentheses. *** 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 year-over-year changes.

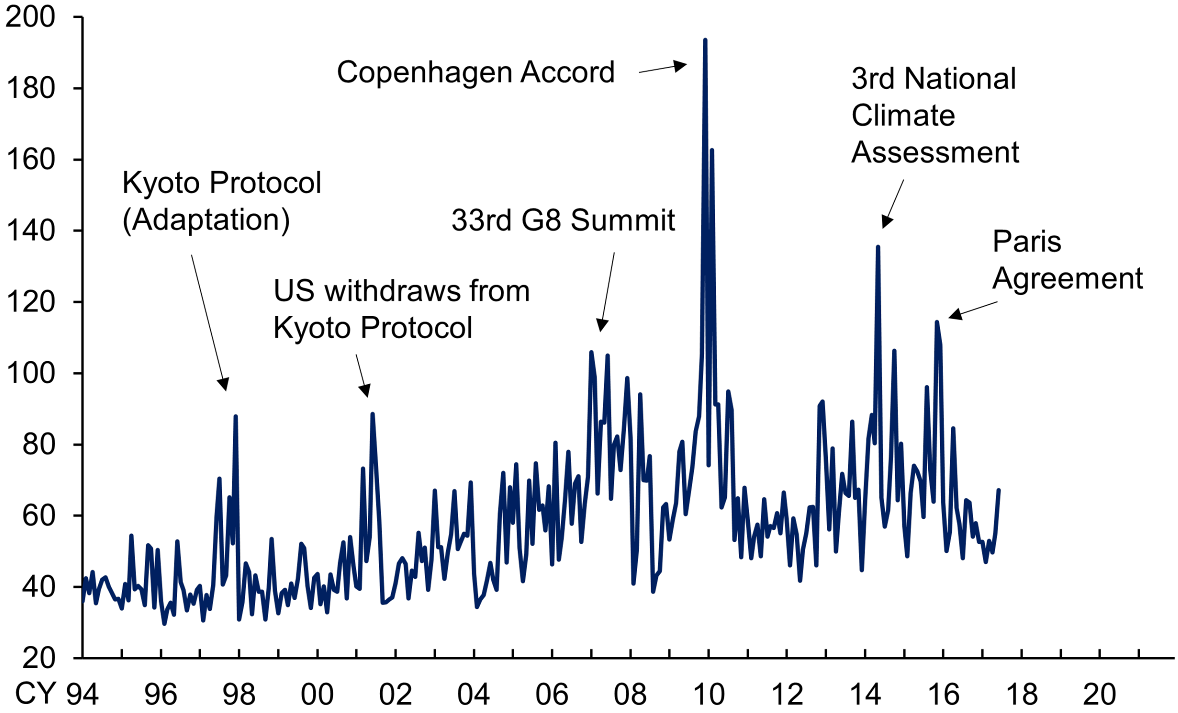

Figure 1: Climate Change News index in the U.S. (WSJ-CCN index)

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 basis points.

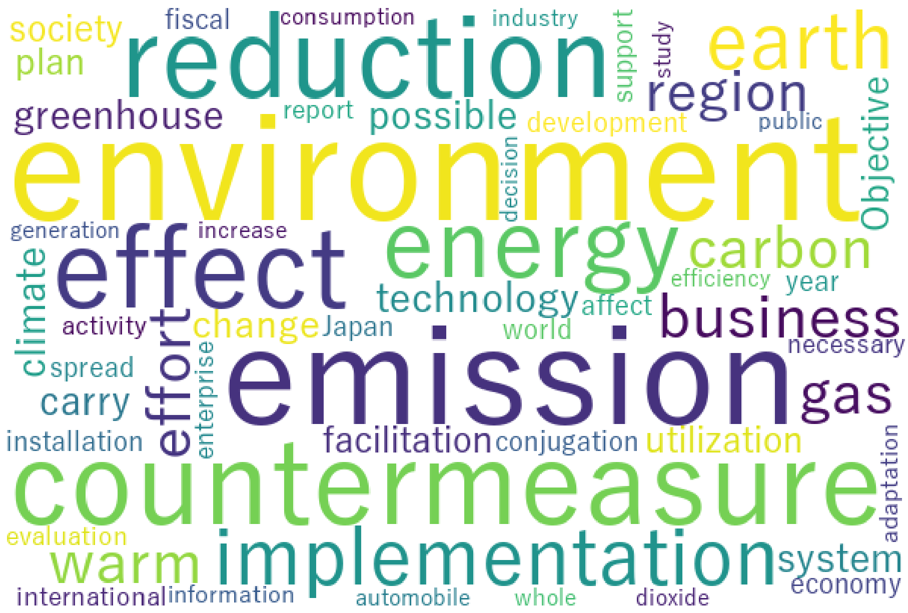

Figure 2: Climate change vocabulary in Japan

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

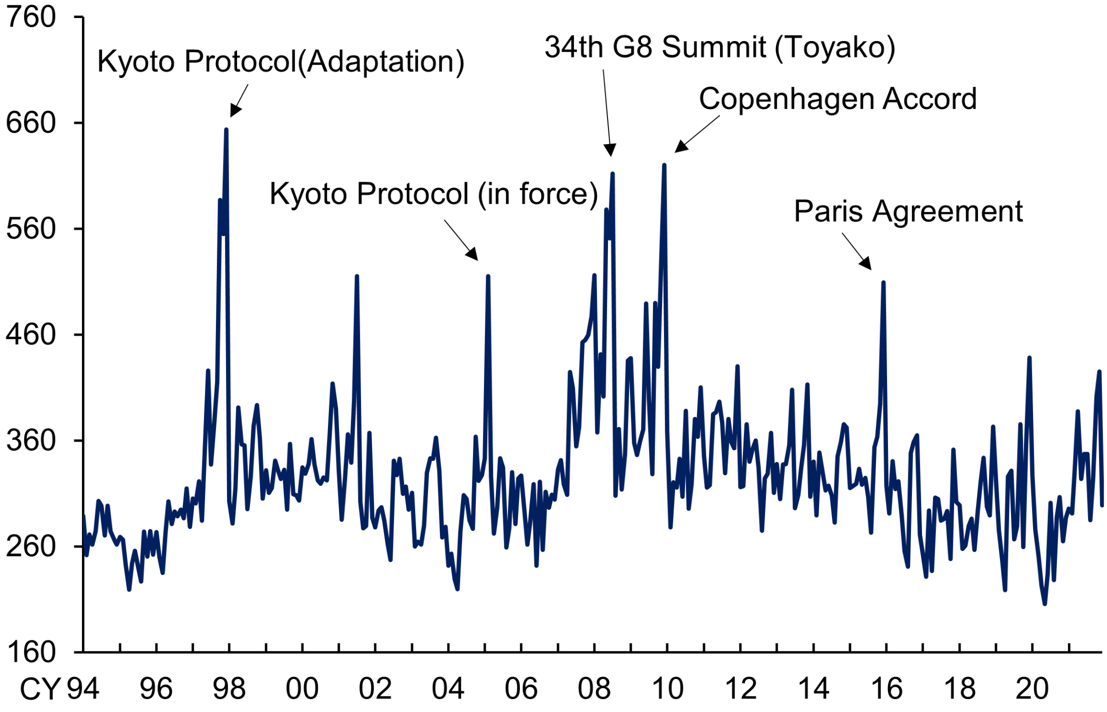

Figure 3: Climate Change News index in Japan

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

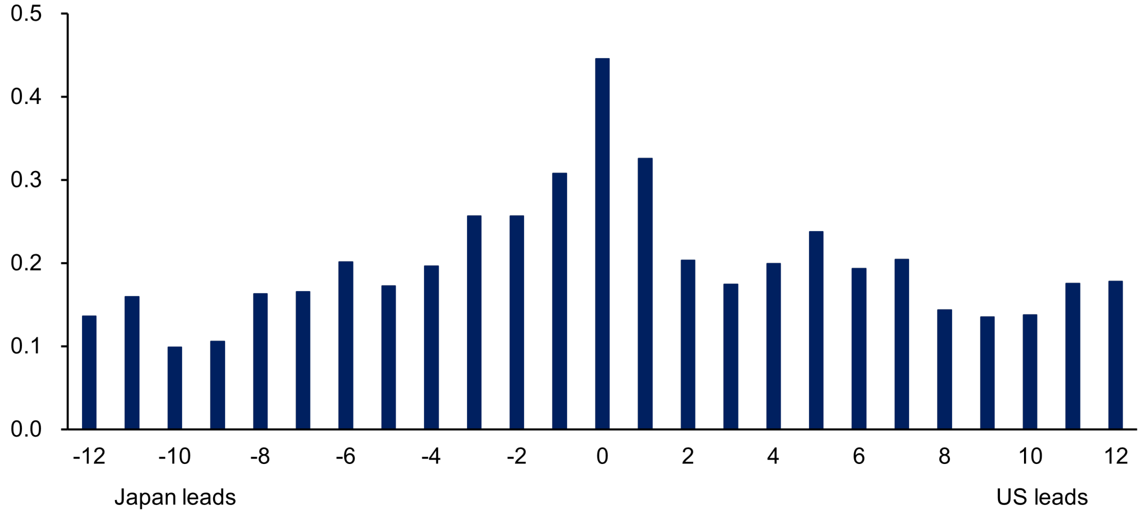

Figure 4: Cross correlation of Climate Change News index in the U.S. and Japan

Notes: The figure indicates cross correlation coefficients of the Climate Change News indexes in the U.S. and Japan at different lags. Sample period is from January 1994 to June 2017.

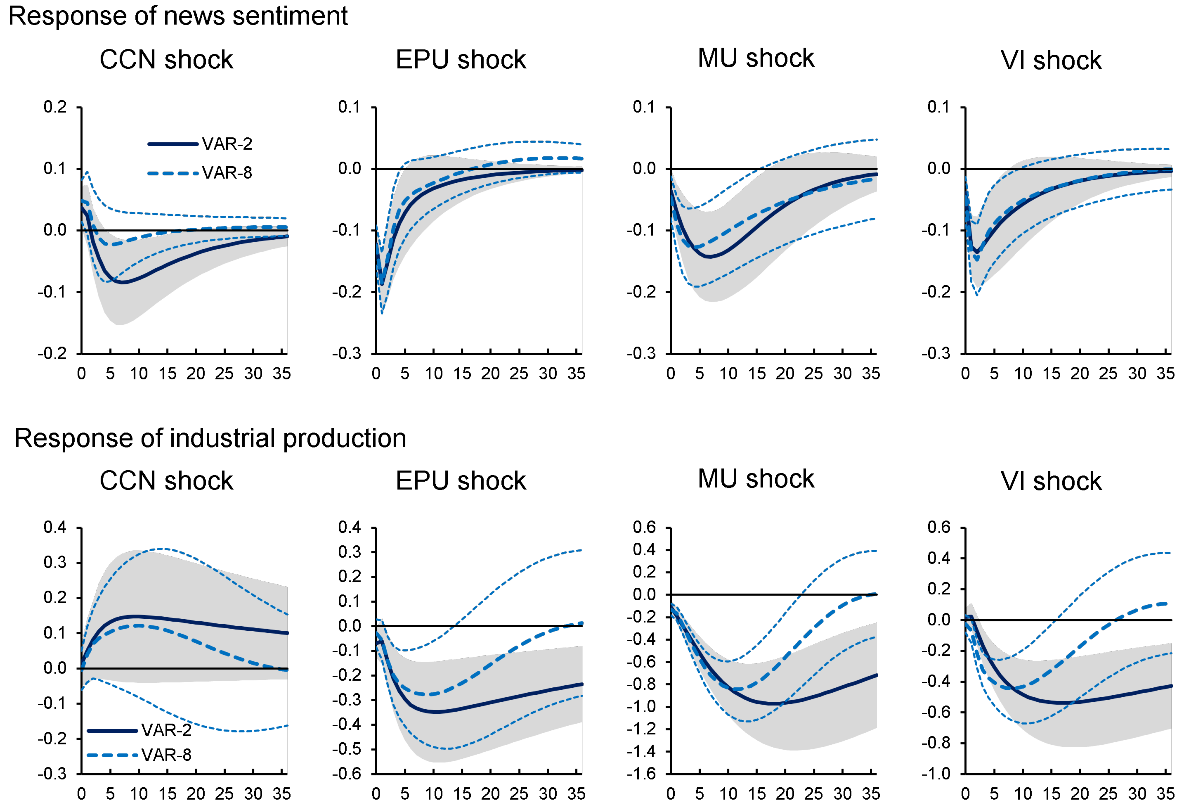

Figure 5: VAR impulse response in the U.S.

Notes: These panels show the impulse responses to a one standard deviation shock. Solid lines are the responses estimated by the bivariate VAR (VAR-2) and dotted lines are those from the eight-variable VAR (VAR-8). The sample period is from January 1994 to June 2017. The shaded area and thin dotted lines indicate the 90 percent confidence bands of VAR-2 and VAR-8 estimates, respectively.

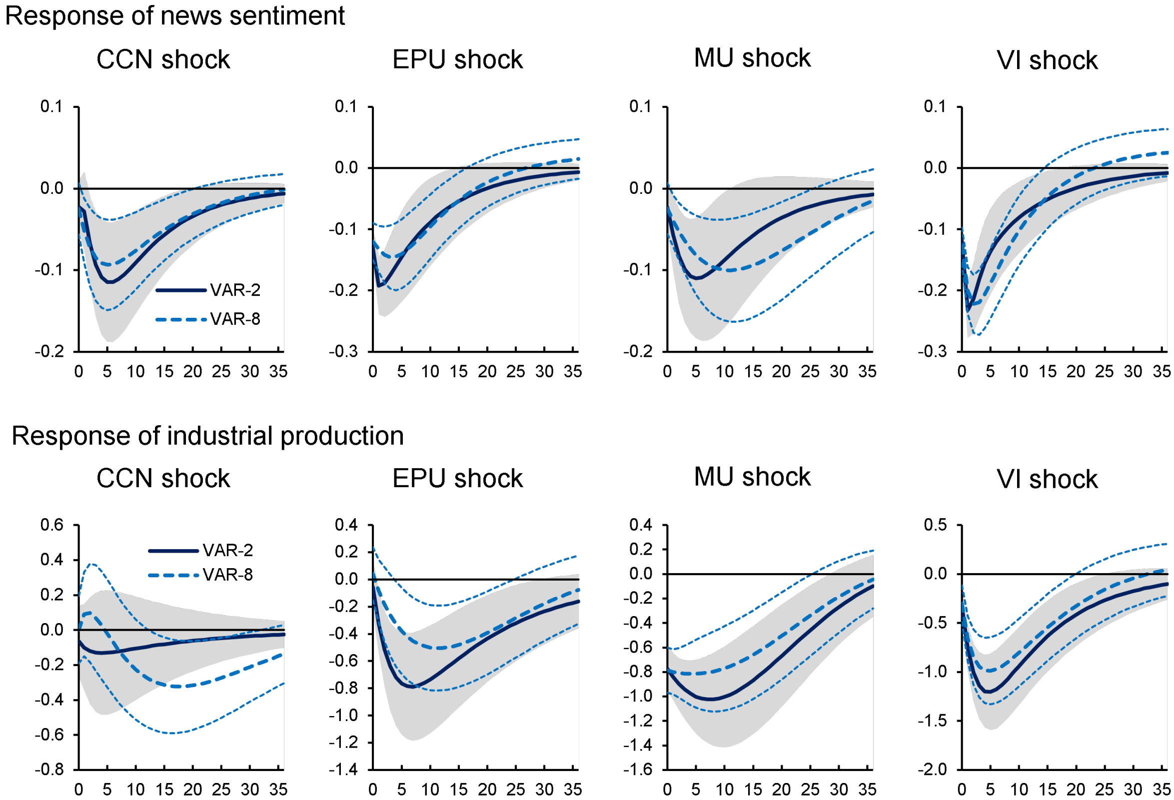

Figure 6: VAR impulse response in Japan

Notes: These panels show the impulse responses to a one standard deviation shock. Solid lines are the responses estimated by the bivariate VAR (VAR-2) and dotted lines are those from the eight-variable VAR (VAR-8). The sample period is from January 1994 to June 2017. The shaded area and thin dotted lines indicate the 90 percent confidence bands of VAR-2 and VAR-8 estimates, respectively.

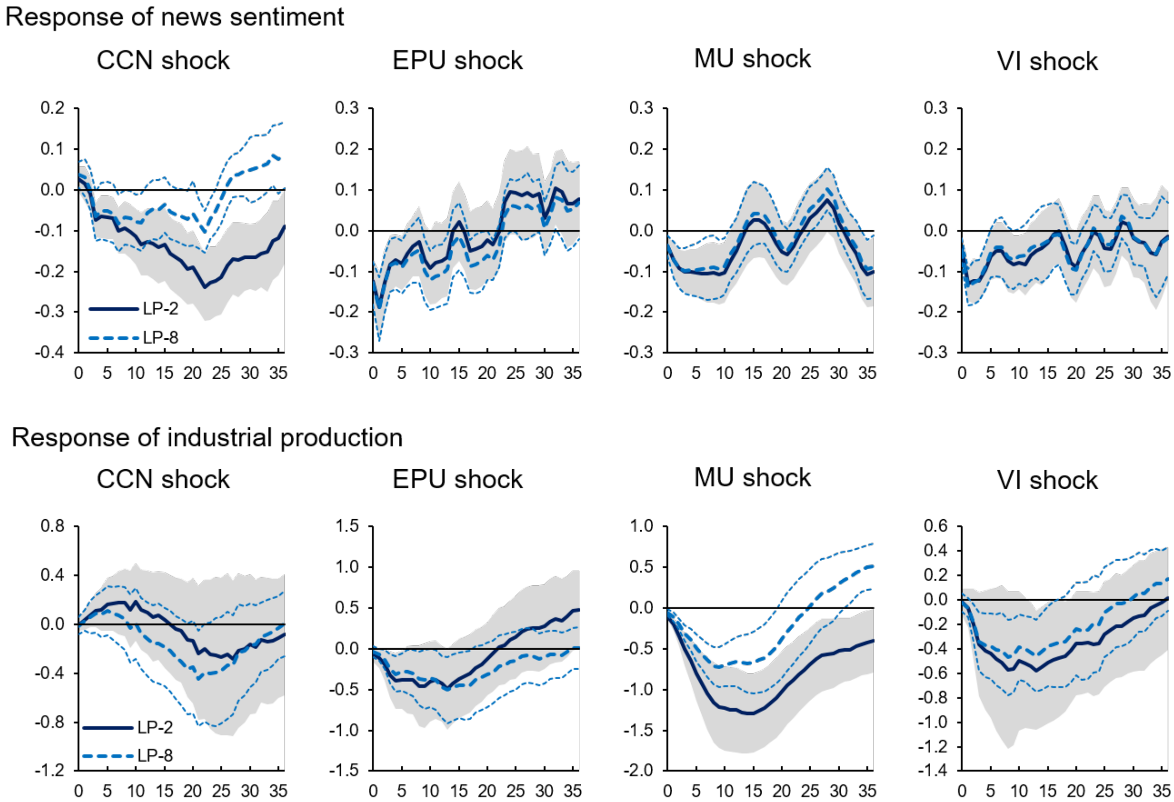

Figure 7: Local Projection impulse response in the U.S.

Notes: These panels show the impulse responses to a one standard deviation shock from local projections. The sample period is from January 1994 to June 2017. The lag length used in local projections (LP-2 and LP-8) is the same as that of the VAR models (VAR-2 and VAR-8). The shaded area and thin dotted lines indicate the 90 percent confidence bands of the LP-2 and LP-8 estimates, respectively.

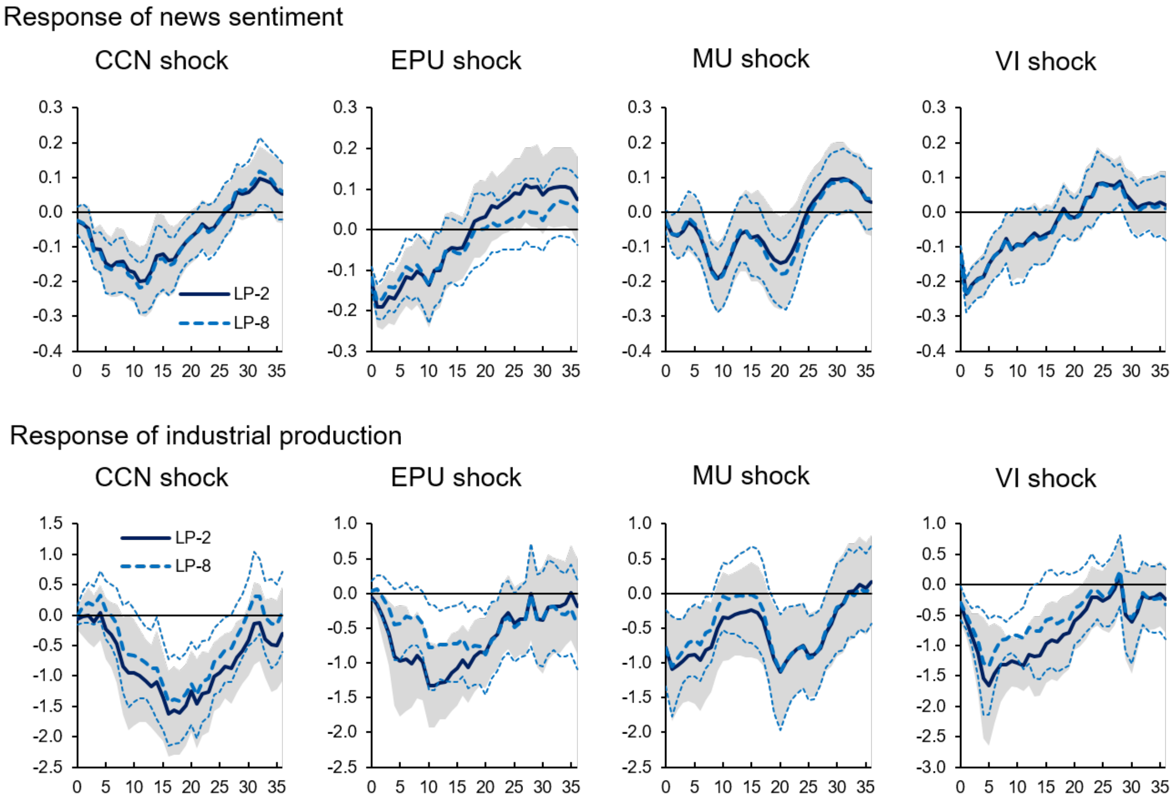

Figure 8: Local Projection impulse response in Japan

Notes: These panels show the impulse responses to a one standard deviation shock from local projections. The sample period is from January 1994 to June 2017. The lag length used in local projections (LP-2 and LP-8) is the same as that of the VAR models (VAR-2 and VAR-8). The shaded area and thin dotted lines indicate the 90 percent confidence bands of the LP-2 and LP-8 estimates, respectively.

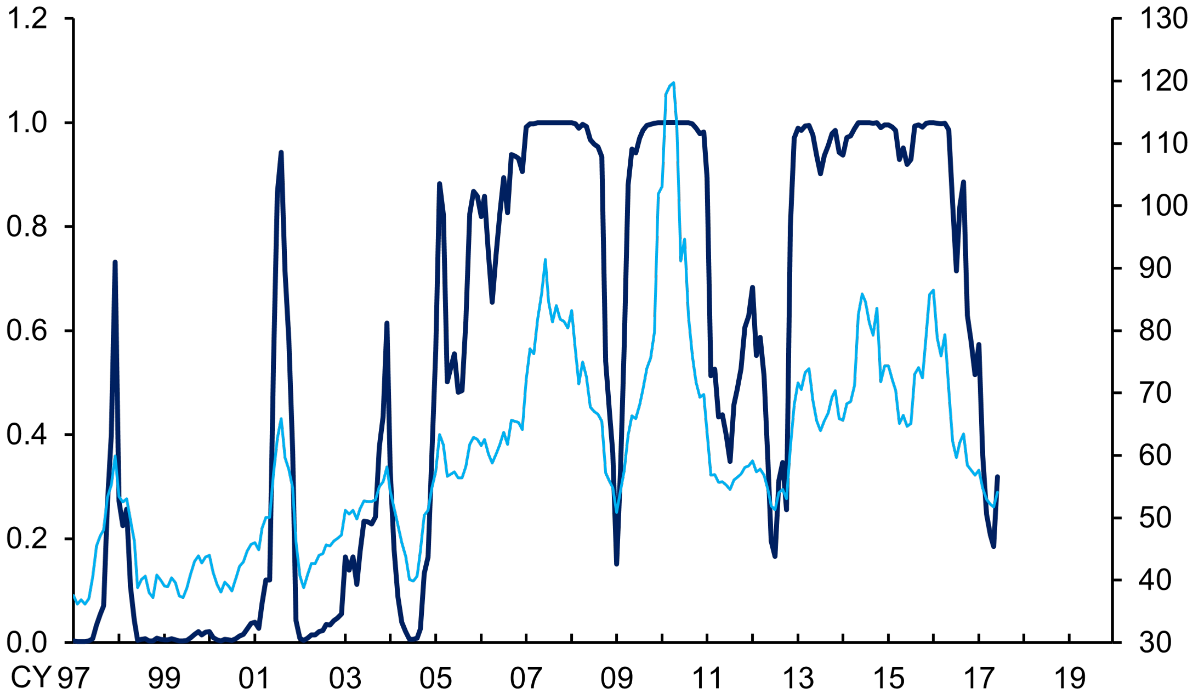

Figure 9: Probability of being in the high attention to climate change regime in the U.S.

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

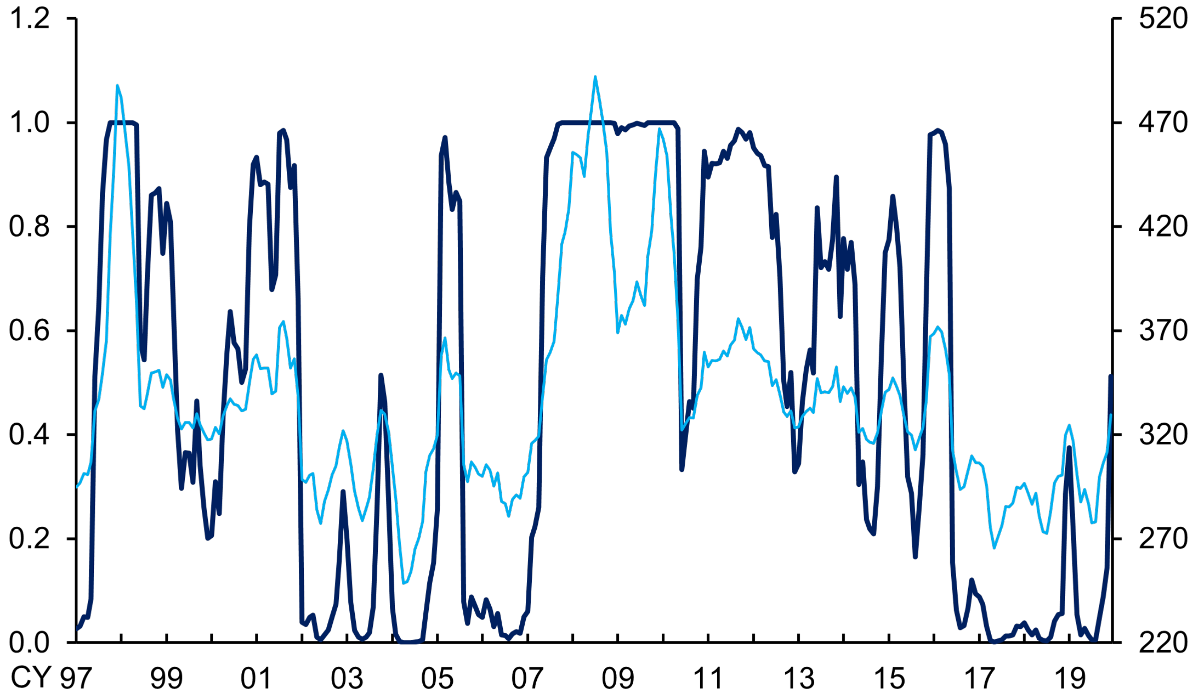

Figure 10: Probability of being in the high attention to climate change regime in Japan

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

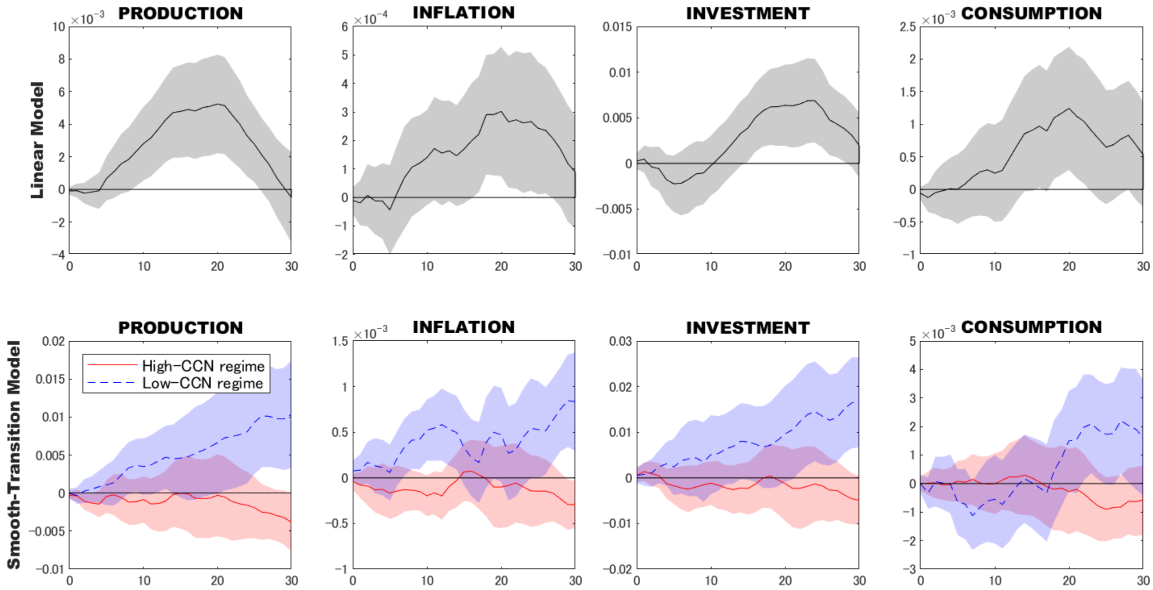

Figure 11: Responses to an expansionary monetary policy shock in the U.S.

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

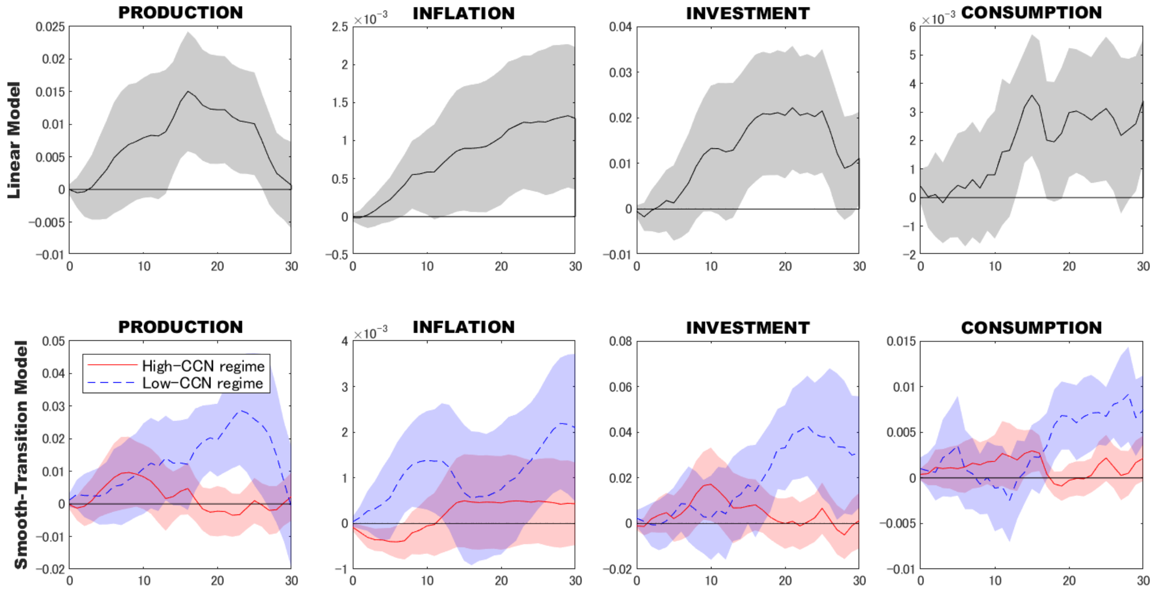

Figure 12: Responses to an expansionary monetary policy shock in Japan

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

A Source of Japanese Climate Change Vocabulary

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

Table A.1: 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)
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, The Nikkei Shimbun, to construct the CCN index. Figure B.1 illustrates the development of the CCN index based on The Nikkei Shimbun which is also one of the major newspapers in Japan. As shown in the figure, our baseline CCN index based on The Mainichi Shimbun is basically consistent with the Nikkei-based CCN index. Also, the correlation between the two indexes is 0.72, and it rises to 0.79 when they are converted to six-months backward moving averages. The high correlation between two indexes indicates that our CCN index is robust in terms of the data source.[16]

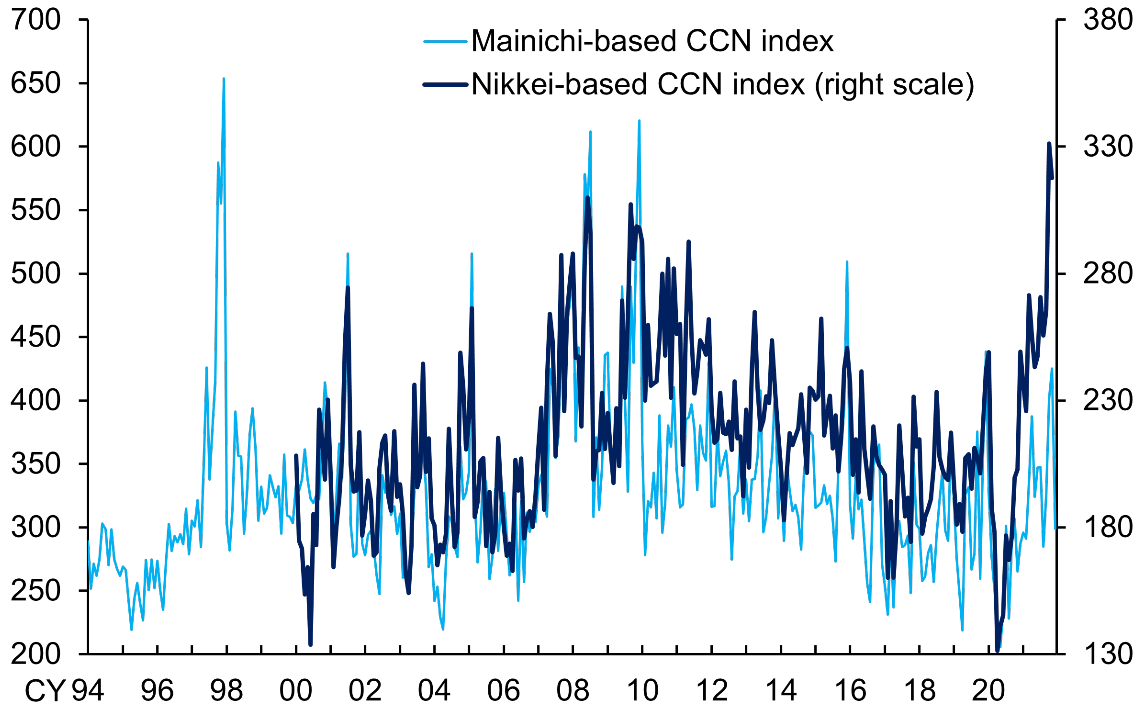

Figure B.1: Japanese CCN index from The Nikkei Shimbun

[16]There are some differences in the development of the indexes. In particular, they differ after 2021, which suggests that the newspapers may have different decision-making processes for how much they report on climate change.

C Robustness check: The regime-dependent transmission of monetary policy shocks

The robustness of our methodology is assessed along several dimensions. We perform 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 the regime variable.

The 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 values of θ. θ determines the intensity of regime-switching and we set $\theta = 5$ in the baseline specification. Figure C.1 for the U.S. and Figure C.2 for Japan show how the results change when we set θ to three or eight. In both figures, the responses to an expansionary monetary policy shock are well within the confidence bands of the baseline estimates, and regardless of the value of θ, the responses of all variables to monetary policy shocks tend to be weaker in high-CCN-attention regimes compared to those in low-CCN-attention regimes. This indicates that the baseline results are robust with respect to the intensity of regime-switching.

The second exercise is to examine if the results are robust when we change the lag length of control variables. The baseline regression Eq.(3) 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 the AIC. We re-estimate our model to check whether our results are robust or not when we change the lag length. Figure C.3 and Figure C.4 show the impulse responses estimated in a regression model with different lag structures for the U.S. and Japan, respectively. Figure C.3 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 when the lag length is three. The estimation results using Japanese data in Figure C.4 show that when the number of lags is twelve, the response of inflation in the high-CCN-attention 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.

The third and the last exercise is to check whether the results vary if we change the length of time for calculating the CCN index moving-average. Figure C.5 shows the results for the U.S. and Figure C.6 shows the results for Japan. They show that the qualitative message of the earlier analysis is unchanged in both the U.S. and Japan.

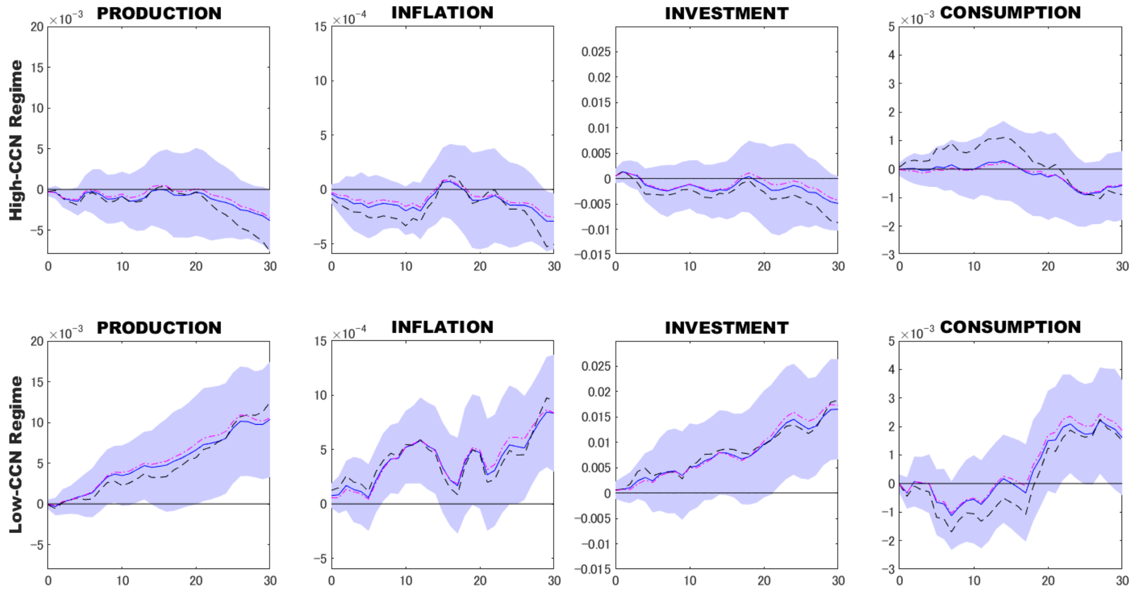

Figure C.1: Robustness to the values of θ in the U.S.

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

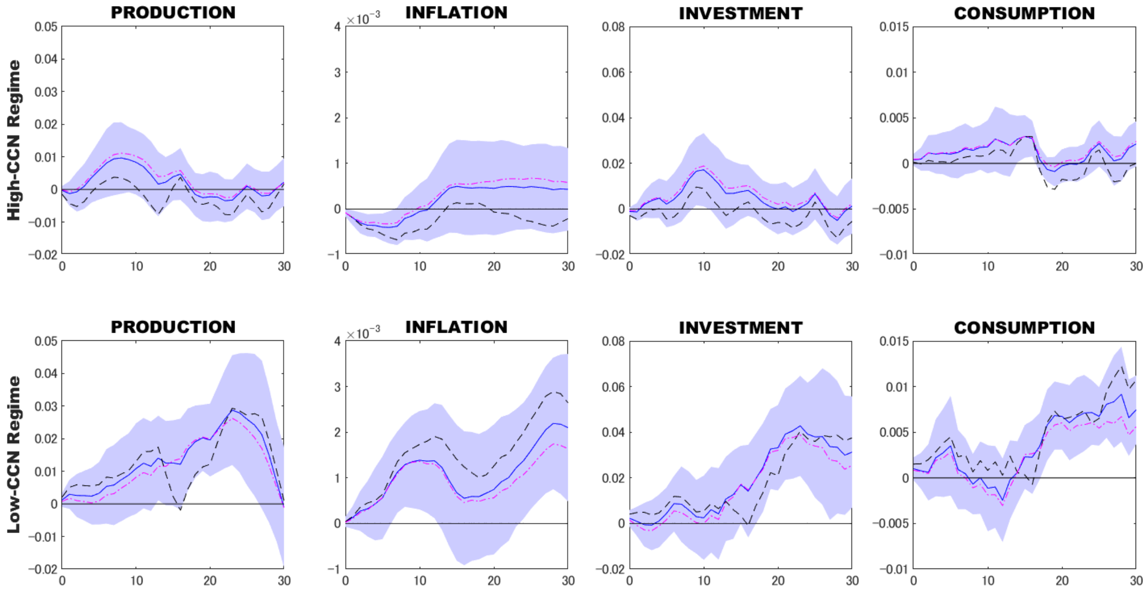

Figure C.2: Robustness to the values of θ in Japan

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

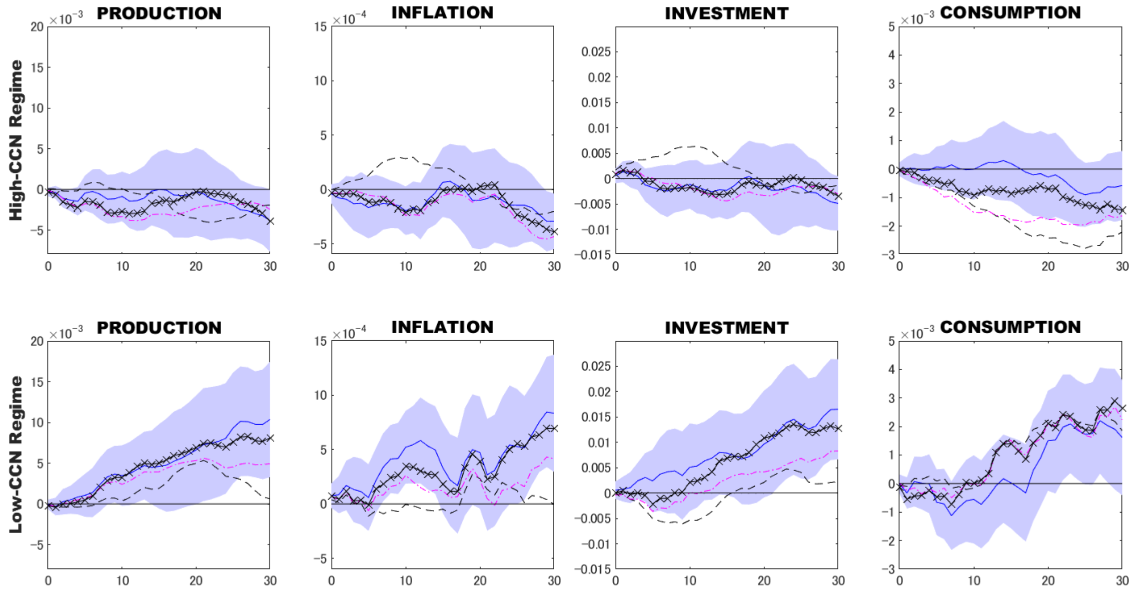

Figure C.3: Robustness to the length of lags of control variables in the U.S.

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

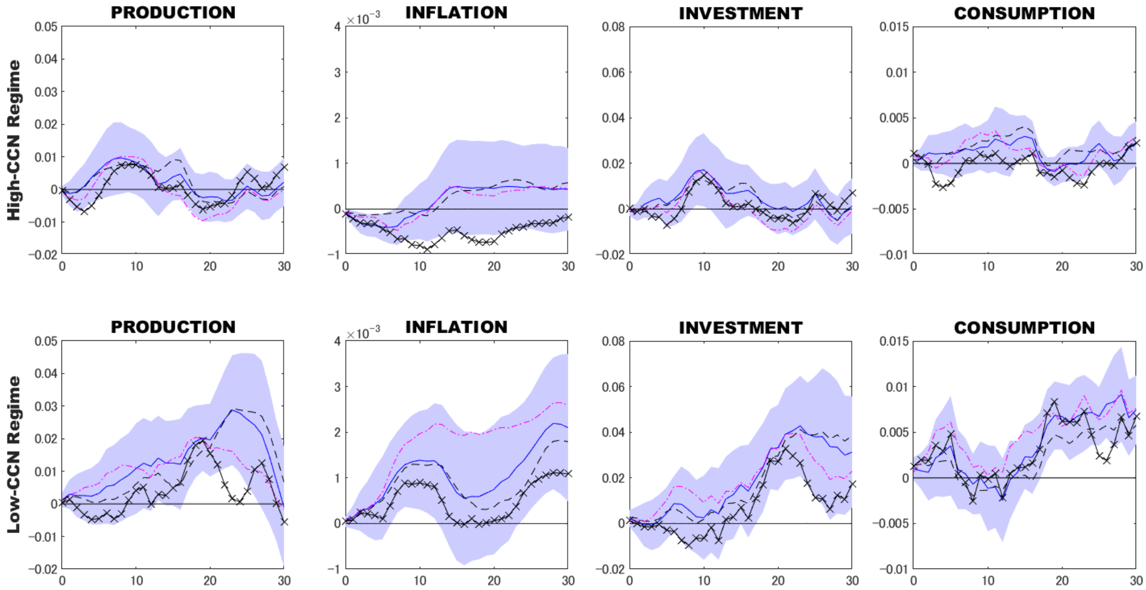

Figure C.4: Robustness to the length of lags of control variables in Japan

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

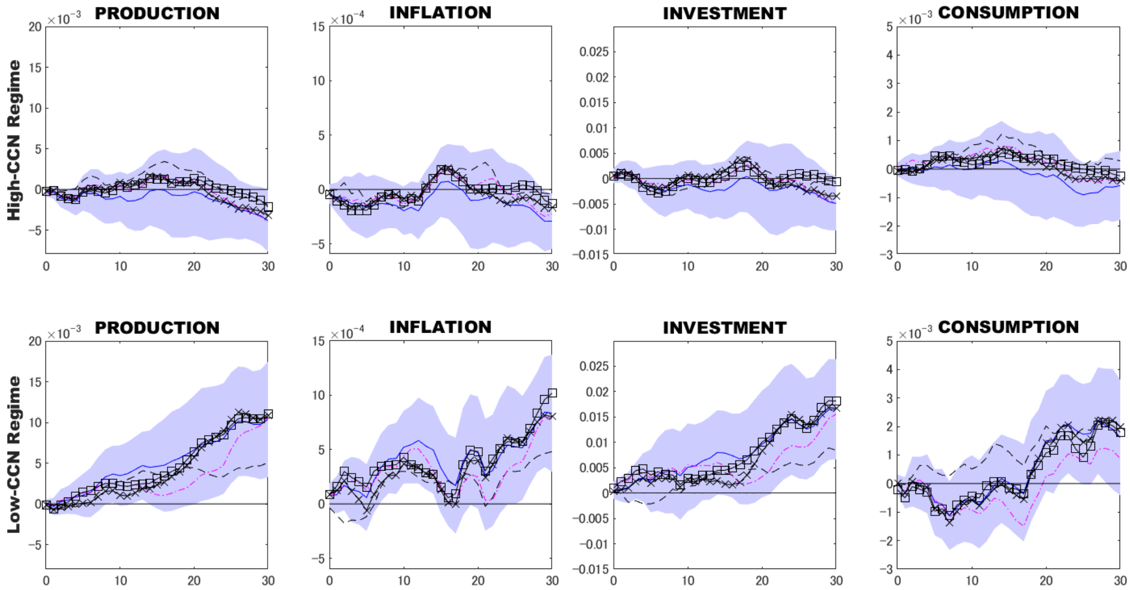

Figure C.5: Robustness to smoothness of the CCN index in the U.S.

Notes: The upper panel shows the responses during the high attention to climate change regime in the U.S. and the lower panel shows the responses during the low attention to climate change regime. The solid line denotes the responses when using a six-month moving average of the CCN index (baseline), the dashed line denotes the responses when using a three-month moving average, the dot-dash line denotes the responses when using a five-month moving average, x denotes the responses when using a seven-month moving average, and the square marker denotes the responses when using a nine-month moving average, respectively. The shaded areas display the 90 percent confidence bands based on Newey and West (1987) standard errors around the baseline responses.

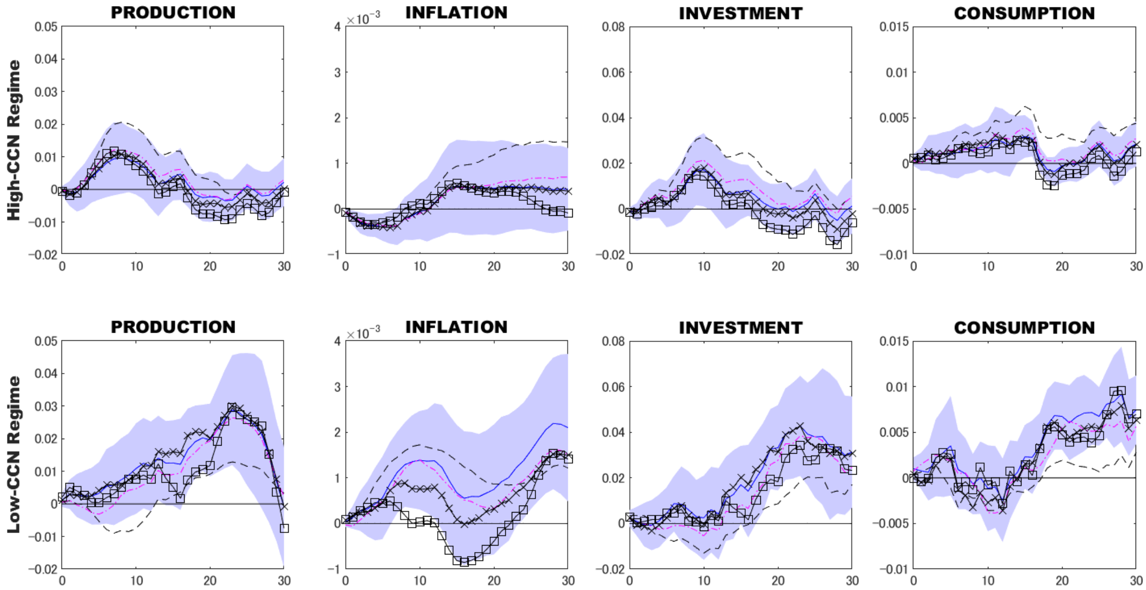

Figure C.6: Robustness to smoothness of the CCN index in Japan

Notes: The upper panel shows the responses during the high attention to climate change regime in Japan and the lower panel shows the responses during the low attention to climate change regime. The solid line denotes the responses when using a six-month moving average of the CCN index (baseline), the dashed line denotes the responses when using a three-month moving average, the dot-dash line denotes the responses when using a five-month moving average, x denotes the responses when using a seven-month moving average, and the square marker denotes the responses when using a nine-month moving average, respectively. The shaded areas display the 90 percent confidence bands based on Newey and West (1987) standard errors around the baseline responses.