HIAS-E-121

Macroeconomic uncertainty matters: A nonlinear effect of financial volatility on real economic activity

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June 2022

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Macroeconomic uncertainty matters: A nonlinear effect of financial volatility on real economic activity*

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Abstract

A stock market volatility index is a widely-used proxy of uncertainty in the macroeconomy, and its increase is shown to dampen real economic activity. In contrast, the macroeconomic uncertainty index proposed by Jurado et al. (2015) measures the predictability of a wide range of macroeconomic indicators and thus is a comprehensive indicator of macroeconomy-wide uncertainty. This paper empirically investigates a nonlinear link between financial volatility and real economic activity depending on the level of the macroeconomic uncertainty index. Based on the United States and Japan data, empirical analysis suggests that an increase in the financial volatility lowers industrial production and business fixed investment more persistently when the macroeconomic uncertainty is higher.

JEL classification: E32, E52.
Key words: Financial volatility, Macroeconomic uncertainty, Nonlinear effect.

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*Financial support from the Ministry of Education, Culture, Sports, Science and Technology of the Japanese Government through Grant-in-Aid for Scientific Research (No.20H00073) and the Hitotsubashi Institute for Advanced Study is gratefully acknowledged.

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1 Introduction

A stock market volatility index is extensively used as a proxy of uncertainty in the financial market. The most popular one is the VIX, conveyed by the Chicago Board Options Exchange, which measures the 30-day expected volatility of the US stock market, derived from S&P 500 call and put options. Existing studies often employ the VIX to gauge not only the financial market uncertainty but also macroeconomy-wide uncertainty, assuming that the financial market uncertainty is correlated with the macroeconomic uncertainty (see, e.g., Bloom, 2009).

Economic theories suggest that an increase in macroeconomic uncertainty reduces real economic activity. Bernanke (1983) and McDonald and Siegel (1986) develop the real option channel in firms' investment decisions. Real option value, which is the value of putting off a decision of irreversible project such as a business fixed investment, would increase as the degree of uncertainty rises, and then firms are more likely to prefer a wait-and-see strategy for the decision making. Leland (1968) proposes the precautionary saving channel, which suggests that households increase their saving to smooth their inter-temporal consumption allocations when they expect a rise in the uncertainty of their future incomes (e.g., Kimball, 1990). Recent studies develop the financial frictions channel (Christiano et al., 2014; Arellano et al., 2019), where a rise in uncertainty increases the default risk of borrowing firms. Then banks shift the increased risk onto the lending rates, which leads to downward pressure on the firm's investments.

On the one hand, the empirical literature exploits the VIX as the indicator of the macroeconomic uncertainty and shows that the increase in the financial volatility exacerbates the real economic activity (e.g., Foerster, 2014; Baker et al., 2016; Castelnuovo et al., 2017). On the other hand, Jurado et al. (2015) propose a novel framework to gauge macroeconomic uncertainty, namely the macroeconomic uncertainty index. It is designed to measure the predictability of a wide range of macroeconomic indicators based on a time-series model. Jurado et al. (2015) define the macroeconomic uncertainty index as an average of time-varying volatilities across the indicators, which gauge a degree of the real-time variance of an unexplained component in the fluctuations of the indicators. The macroeconomic uncertainty index is significantly correlated with real economic activity and thus is a valuable indicator of macroeconomy-wide uncertainty (e.g., Nam et al., 2021; Reif, 2021).

Shinohara et al. (2020) show that the financial volatility and the macroeconomic uncertainty index are correlated to some extent, though they are sometimes disconnected. This evidence suggests that each of the uncertainty indices contains unique information that could be related to real economic activity. If so, incorporating both indices into the empirical model helps us predict the future course of the economy better. However, little is known about the characteristics of the relationship between financial volatility and macroeconomic uncertainty and their specific information content.

To fill the gap this study investigates whether the impact of financial volatility on real economic activity depends on the level of macroeconomic uncertainty. Extending the empirical model that assesses the negative relationship between the financial volatility and the real economic activity, the analysis examines whether the macroeconomic uncertainty index contains additional information about the real economic activity. We formulate a nonlinear effect of the financial volatility whose impact depends on regimes of high and low macroeconomic uncertainty and estimate the effect using data for the United States and Japan.

As the financial volatility reflects market sentiments such as the degree of risk aversion, the stock market generally reacts to news shocks more vividly than the real economic activity. The financial volatility also responds to macroeconomic shocks as they materialize in the macroeconomic uncertainty. The focus of this paper is whether the influence of financial volatility on the real economic activity depends on the macroeconomic environment, in particular, the degree of uncertainty in terms of the future course of real economic activity. In a high-level macroeconomic uncertainty regime, the increase in financial volatility could affect real economic activity more severely than in a low-level uncertainty regime. This paper tests this nonlinear relationship between financial volatility and real economic activity triggered by the level of macroeconomic uncertainty.

As a related study, Jurado et al. (2015) assess differences between the macroeconomic uncertainty index and financial volatility in terms of time series property and contribution to explaining the future course of real economic activity. However, the analysis does not examine the interaction of the two uncertainty indices. From a theoretical perspective, Aït-Sahalia et al. (2021) develop a novel asset pricing model in which the uncertainty in the stock market return and its volatility are both stochastic, and their degree of connection is also stochastic. In such a situation, the model that takes account of a disconnect between volatility and uncertainty significantly improves portfolio performance.

The remainder of the paper is organized as follows. Section 2 explains the macroeconomic uncertainty index. Section 3 describes the econometric method and data used in the empirical analysis for the United States and Japan. Section 4 provides an empirical analysis of the nonlinear impact of the financial volatility on industrial production and business fixed investment. Section 5 concludes.

2 Macroeconomic uncertainty index

The macroeconomic uncertainty index is based on forecast errors of predicted values derived by a time series model on various macroeconomic indicators. This index assumes that economic decision-making depends on how less predictable the economy has become. When the economy's future course gets less predictable, we interpret that the economy becomes more uncertain. Jurado et al. (2015) use 132 monthly indicators collected from seven categories: production, labor market, consumption, and so on. The index aims to comprehensively capture the uncertainty caused by various factors underlying the macroeconomy.

For each macroeconomic indicator, denoted by y_{jt}, for $t = 1, \ldots, T$, where j denotes the series, one-period ahead uncertainty is represented by the conditional volatility of forecasted error, namely,

$$\mathcal{U}_{j,t+1} = \sqrt{\mathrm{E}\left[\left(y_{j,t+1} - \mathrm{E}\left[y_{j,t+1}|I_t\right]\right)^2 |I_t\right]}, \tag{1}$$

where I_t is the information set available at period t. When the squared error in forecasting $y_{j,t+1}$ rises, uncertainty of this macroeconomic indicator increases. To construct the uncertainty index for macroeconomy overall, denoted by MU_t, we simply take the average of the conditional volatilities for all the macroeconomic indicator, as

$$\mathrm{MU}_t = \frac{1}{N}\sum_{j=1}^{N}\mathcal{U}_{j,t+1},$$

where N is the number of macroeconomic indicators. Jurado et al. (2015) generalize the idea to an h-period ahead uncertainty for $h = 1, 2, \ldots$. In the current paper, we use the index with $h = 1$ for simplicity.

To obtain estimates of equation (1), we develop a time-series forecasting model where each macroeconomic indicator is forecasted using information from the histories of all the macroeconomic indicators available in the analysis. We extract common factors from the macroeconomic indicators and develop a linear regression whose explanatory variables are the common factors and own lags of the indicator. Then given the forecasted errors computed from the forecasting model, we estimate a stochastic volatility model to obtain time-varying volatility in the errors of the one-period ahead forecasting. The stochastic volatility model has been widely used in financial econometrics (e.g., Shephard, 2005) and recently in macroeconometrics (e.g., Primiceri, 2005; Stock and Watson, 2007). Using the estimated stochastic volatility and parameters in the model, we compute the estimate of equation (1).

The macroeconomic uncertainty index for the United States is downloadable on Sydney Ludvigson's website. For Japan, Shinohara et al. (2020) propose a Japan's macroeconomic uncertainty index following the method of Jurado et al. (2015). The current paper slightly modifies Japan's dataset due to the availability of data. The detail of computing the macroeconomic uncertainty index for Japan is described in Appendix.

3 Empirical model and data

3.1 Local projection methods

We use the local projection methods (Jordà, 2005) to estimate the nonlinear impact of the financial volatility on real economic activity. The empirical model is given by

$$y_{t+h} \;=\; \alpha_h + \phi_h y_{t-1} + \beta_h V_t + \gamma_h V_t \times I[M_t > \bar{M}] + \boldsymbol{\delta}_h \boldsymbol{x}_{t-1} + \varepsilon_{ht}, \tag{2}$$

for $h = 0, 1, \ldots, H$, where y_t is the variable of real economic activity. In the following empirical analysis, we focus on industrial production and the business fixed investment as the variable y_t. For the uncertainty indices, V_t denotes the index for financial volatility, M_t denotes the macroeconomic uncertainty index, $\bar{M}$ is a threshold for the macroeconomic uncertainty index, which generates the nonlinearity of the relationship between y_{t+h} and V_t. $I[\,\cdot\,]$ denotes the indicator function that takes the value of one when the argument is true and zero otherwise. $\boldsymbol{x}_{t-1}$ is the vector of explanatory variables other than the uncertainty index. The frequency of the model is monthly for the analysis of industrial production and quarterly for the business fixed investment.

The coefficient β_h measures the impact of the financial volatility on the real economic activity when the macroeconomic uncertainty is low. The coefficient γ_h assesses an additional effect of the financial volatility that arises when the macroeconomic uncertainty becomes higher than the threshold. We set $\bar{M}$ as the time-series mean of M_t. The linear regression is estimated by the ordinary least squares for each horizon h.

3.2 Data

We use the VIX for the United States for the financial volatility, downloaded from FRED of the St. Louis Fed. The series is originally provided by Chicago Board Options Exchange (CBOE). For Japan, we use the Volatility Index for Japan (VXJ) provided by the VXJ research group at the Center for Mathematical Modeling and Data Science, Osaka University. The VXJ is the implied volatility of the stock price index Nikkei 225. We convert the daily series of these stock market volatility indices to monthly series by taking a simple daily average.

For the financial volatility indices and the macroeconomic uncertainty indices, we divide the series by its standard deviation. This standardization makes the interpretation of the estimates easier in the following analysis. In this setting, the coefficient of the financial volatility in equation (2) indicates the impact of a one-standard-deviation change in the financial volatility on the real economic activity.

We use the total index of industrial production, seasonally adjusted. We use the real gross private domestic investment for the business fixed investment, which is also seasonally adjusted. We use the stock price indices S&P 500 and TOPIX (Tokyo Stock Price Index) for the explanatory variable in analyzing the business fixed investment for the United States and Japan, respectively. The stock price is employed as is consistent with Tobin's Q theory as in the previous studies. We take the natural logarithm for these variables in the estimation. We take a three-month average to convert all the variables explained here to the quarterly series in the analysis of the business fixed investment.

The sample period is from January 1998 to December 2021. We set this period because the VXJ is available only from January 1998. Because the variables are considerably volatile during the spread of COVID-19 in 2020, the baseline result is obtained on the sample period up to December 2019. The robustness of the result is examined using the data extended to December 2021.

4 Empirical analysis

4.1 The uncertainty indices

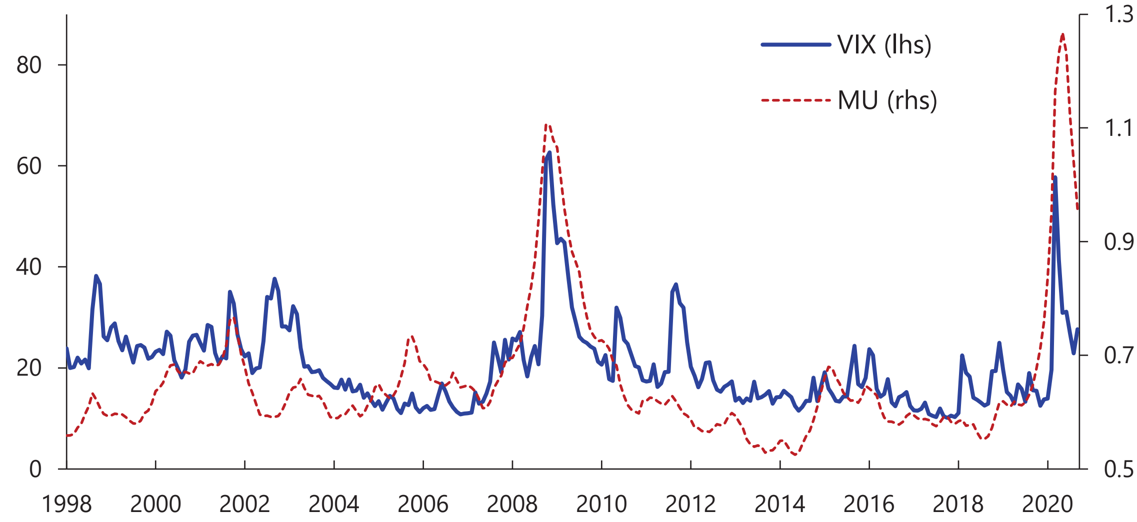
Figure 1 plots the monthly series of the stock market volatility and the macroeconomic uncertainty indices (hereafter, MU) for the United States and Japan. Overall, both series look similar, while each has several notable fluctuations. For the United States, the VIX and the MU hiked simultaneously around 2008–2009 when the global financial crisis (GFC) hit the economy. Also, they both increased remarkably in 2020 due to the spread of COVID-19. In contrast, the VIX rose multiple times in the early 2000s and the early 2010s, while the MU stayed at a low level except for the increase in 2001, reflecting the turmoil when the IT bubble busted. In 2020, it is notable that the VIX decreased quickly after its peak, while the MU further increased and peaked later.

For Japan, the correlation between the two uncertainty indices is lower than that for the United States, as pointed out by Shinohara et al. (2020). The VXJ and the MU rose markedly around 2008–2009 and 2020 in the same manner as the United States. Still, we observe several notable increases in the MU, reflecting, for example, the massive earthquake in 2011 and the increasing trade tension between the United States and China in 2019.

We test whether two uncertainty indices have a lag and lead relationship by computing the time-lagged correlation coefficient between two series, as reported in Figure 2. The correlation peaks at the simultaneous relation for both the countries, which indicates that the two indices do not have a significant lag and lead relationship. While the correlations that the MU leads the VIX are slightly higher than those that the VIX leads the MU, their difference is not statistically significant at the 5% significance level.

Figure 1: Stock market volatility (VIX for the United States and VXJ for Japan) and the macroeconomic uncertainty index (MU).

(a) United States



(b) Japan

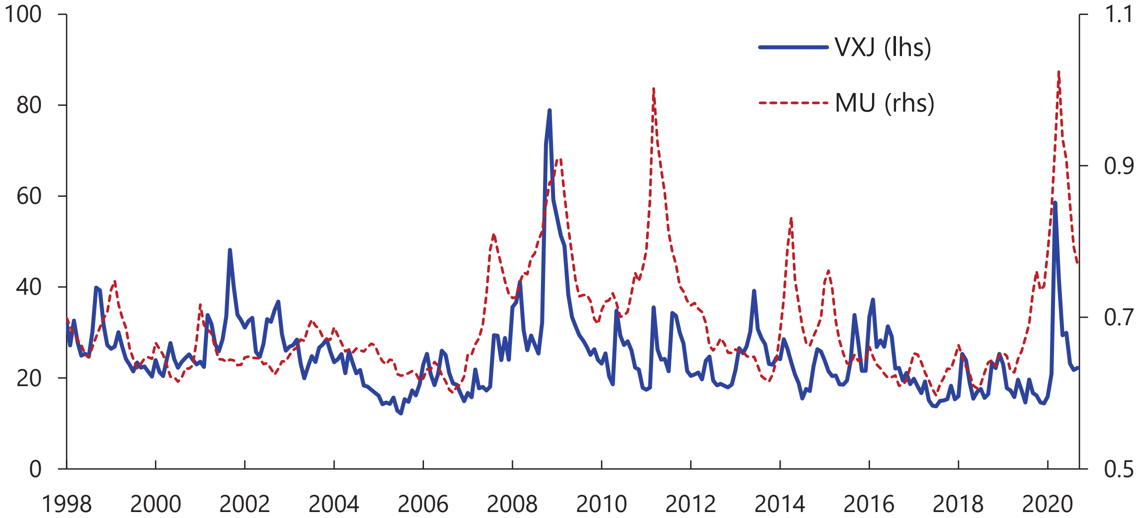
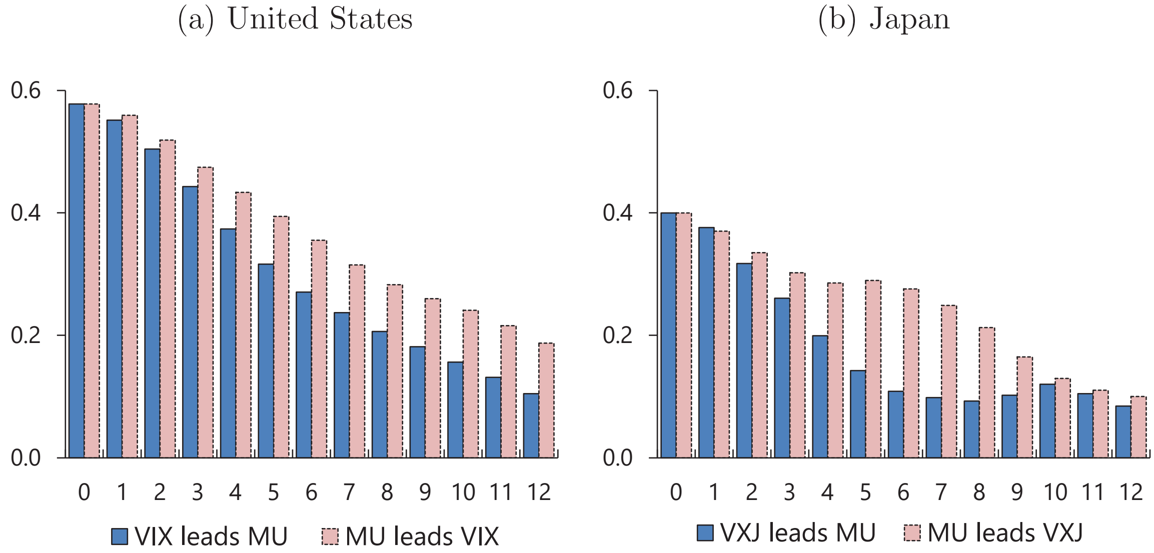


Figure 2: Time-lagged correlation between stock market volatility (VIX for the United States and VXJ for Japan) and the macroeconomic uncertainty index (MU). The horizontal axis indicates months for the lags.



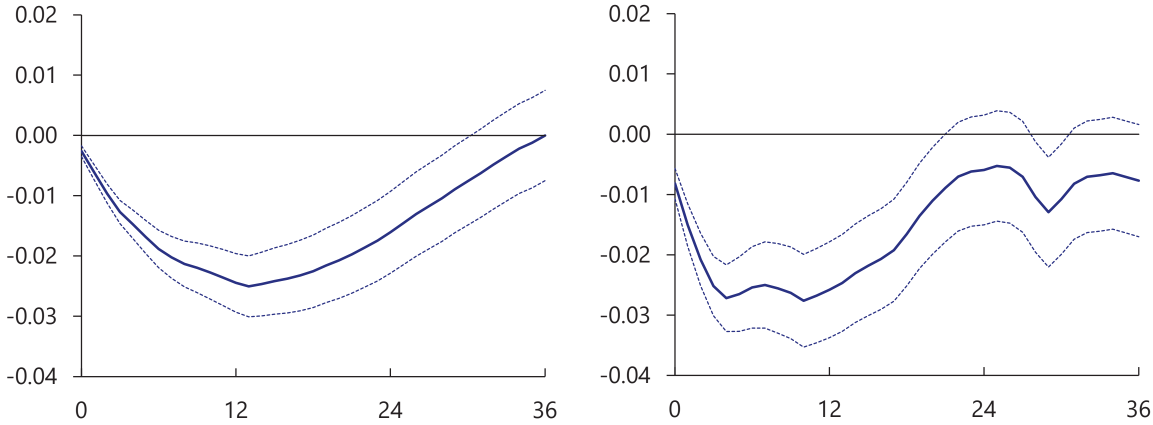
4.2 Nonlinear effect of the financial volatility

First, we estimate equation (2) with the monthly series of industrial production, excluding the nonlinear term of the coefficient γ_h. For simplicity, no explanatory variable other than the uncertainty index is considered. Figure 3 plots the estimation result showing the estimates of coefficient β_h for $h = 0, \ldots, 48$ with its 95% confidence intervals. The estimate, which measures the impact of the financial volatility on industrial production, is significantly negative for both the United States and Japan.

Next, we estimate the model including the nonlinear term in equation (2). Figure 4 plots the estimated impact of the financial volatility when the macroeconomic uncertainty is low and the result of the additional effect when the macroeconomic uncertainty is high. The estimates show that the low-regime impact is short-lived as the response reaches its bottom around 4–13 months, as observed in the preliminary result above. In contrast, the latter impact is remarkably persistent as the estimate is significantly negative even after two years. Notably, this finding is obtained for both countries. The result implies that when the macroeconomic uncertainty is high, the additional impact of the financial

Figure 3: Estimated impacts of the financial volatility on industrial production. The dotted lines indicate the 95% credible intervals. The horizontal axis refers to months.

(a) United States (b) Japan



volatility on industrial production is negative and considerably persistent.

The quarterly series of the business fixed investment is examined similarly. Industrial production and stock price are incorporated as the explanatory variables. Figure 5 plots the result of local projection without the nonlinear term. The rise in financial volatility significantly dampens the business fixed investment for both countries. The response of the investment reaches its bottom around 6–9 quarters.

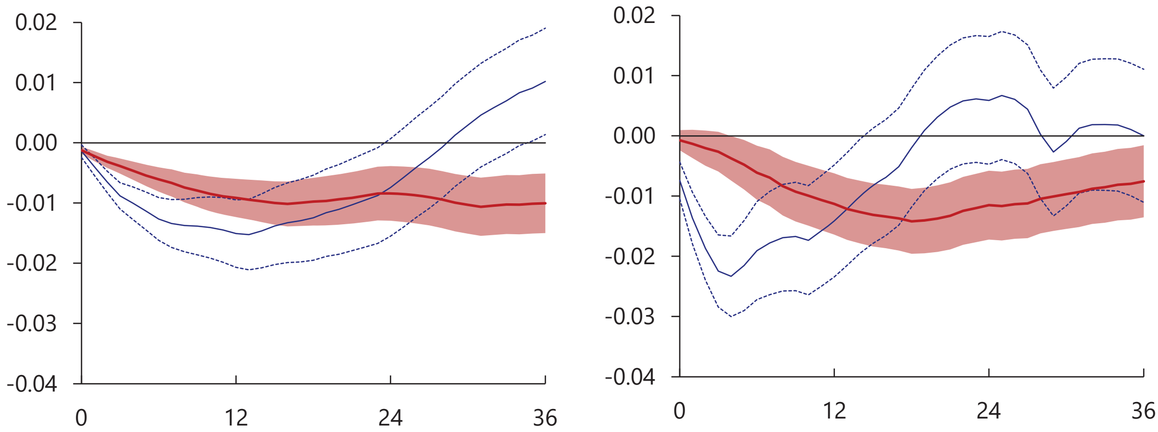
Figure 6 shows the estimates with the nonlinear term. The impact of the financial volatility is more persistent in the regime of high macroeconomic uncertainty than that in the low uncertainty regime. The response in the high uncertainty regime reaches its bottom around 10–12 quarters, while that in the low uncertainty does around 4–7 quarters. Remarkably, this finding is obtained in both countries.

4.3 Robustness

We conduct robustness checks regarding the sample period, using the empirical model for the monthly industrial production series. Note that the sample period for the baseline result is obtained from January 1998 to December 2019. First, we extend the sample up to December 2021, including the period of the spread of COVID-19. Second, we limit

Figure 4: Estimated nonlinear impacts of the financial volatility on industrial production. The solid (blue) and bold (red) lines are the impacts when the macroeconomic uncertainty is low and high, respectively. The dotted lines and the shaded area indicate the 95% credible intervals. The horizontal axis refers to months.

(a) United States (b) Japan



the sample period to the late 2000s and the 2010s: specifically, using the sample period from January 2007 to December 2019.

Figure 7 shows the estimation result for the different sample periods. While only the mean estimates are plotted without confidence intervals in the figure, we find that the impact of financial volatility on industrial production is statistically significant in all the cases. The result suggests that the difference between the low and high regimes of macroeconomic uncertainty is evident: the mean response in the high uncertainty regime is more persistent than in the low uncertainty regime. We confirm the baseline result is robust for both countries.

Figure 5: Estimated impacts of the financial volatility on the business fixed investment. The dotted lines indicate the 95% credible intervals. The horizontal axis refers to quarters.

(a) United States (b) Japan

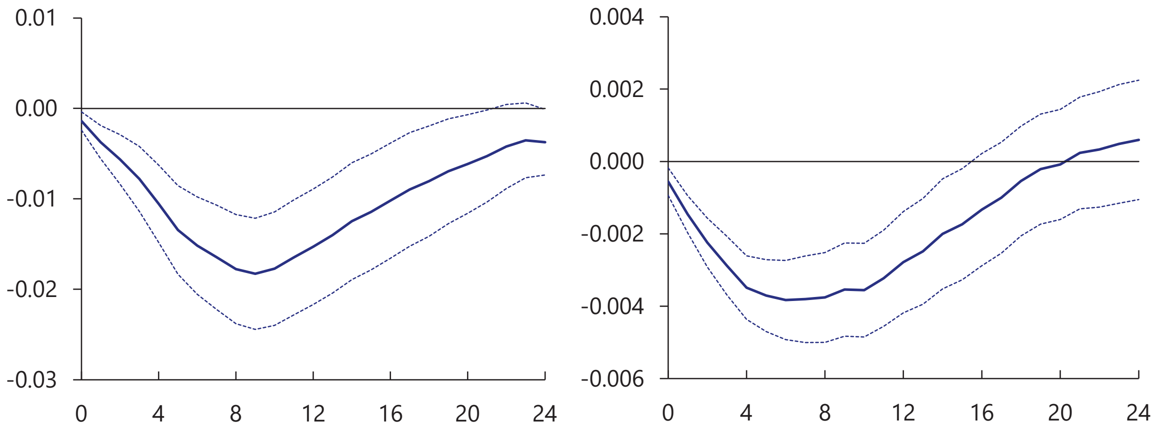


Figure 6: Estimated nonlinear impacts of the financial volatility on the business fixed investment. The solid (blue) and bold (red) lines are the impacts when the macroeconomic uncertainty is low and high, respectively. The dotted lines and the shaded area indicate the 95% credible intervals. The horizontal axis refers to quarters.

(a) United States (b) Japan

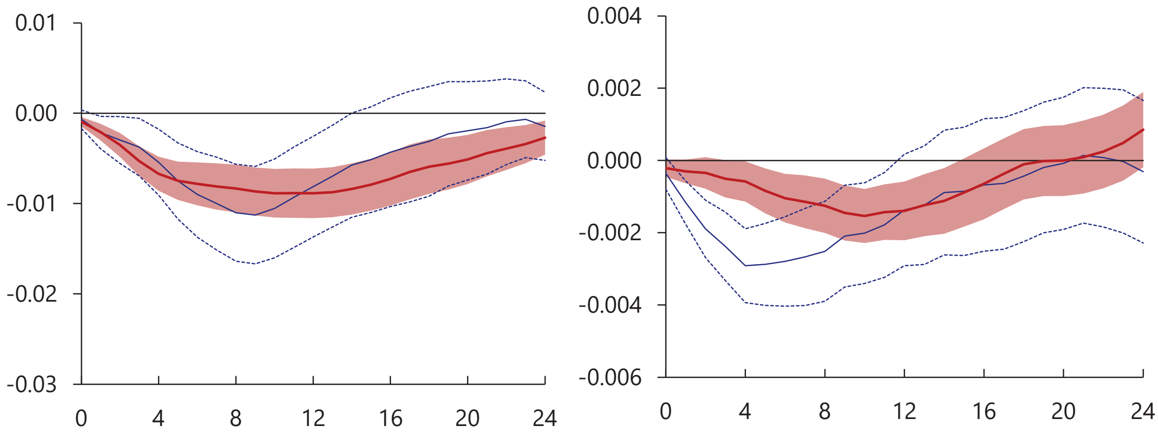
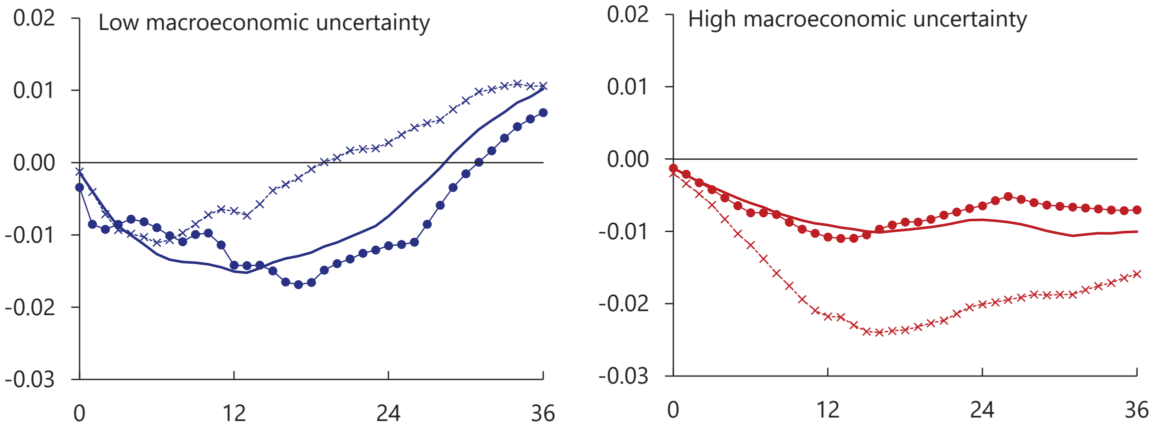
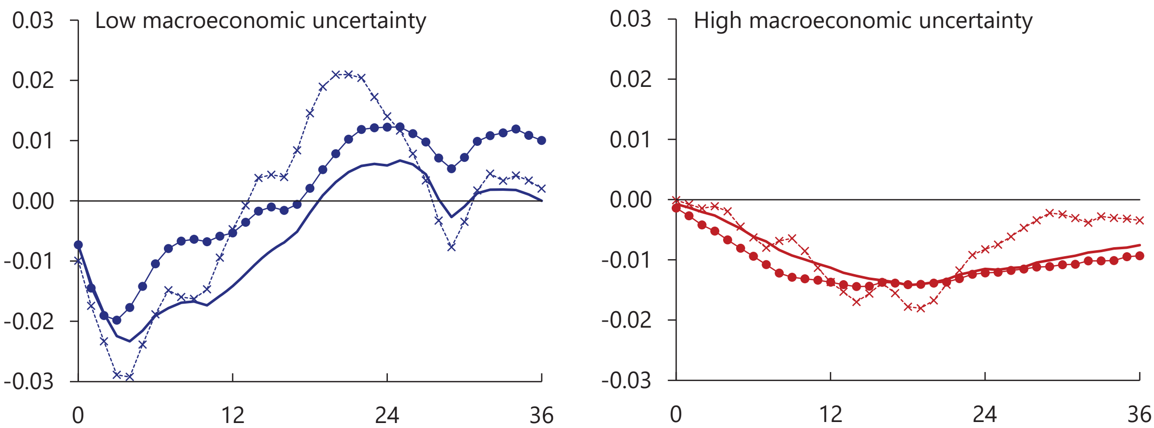


Figure 7: Robustness check: Estimated nonlinear impacts of the financial volatility on industrial production. (i) The bold line is the mean estimate from the baseline sample period, from January 1998 to December 2019; (ii) the solid line with circles is the estimate based on data up to December 2021; (iii) the dotted line with crosses is from January 2007 to December 2019. The horizontal axis refers to months.

(a) United States



(b) Japan



5 Concluding remarks

This paper investigates the nonlinear impact of financial volatility on real economic activity, which depends on the level of macroeconomic uncertainty. Using the United States and Japan data, the nonlinear effect is assessed by the local projection methods. The response of industrial production and the business fixed investment to the rise in the stock market volatility is significantly negative. This response appears to be more persistent when the macroeconomic uncertainty is high than that when the macroeconomic uncertainty is low.

In the literature, other uncertainty indices such as the economic policy uncertainty index (EPU) of Baker et al. (2016) and those based on disagreements among professional forecasts on the economic indicators (e.g., Lahiri and Sheng, 2010; Bachmann et al., 2013) have attracted attention. It is of interest to explore what unique information these indicators have in terms of the impact on real economic activity relative to the stock market volatility and macroeconomic uncertainty index. This leaves as future work.

Appendix. Computation method for the macroeconomic uncertainty index for Japan

Jurado et al. (2015) propose the macroeconomic uncertainty index (MU) for the United States. This appendix documents the procedure to compute Japan's MU.

Shinohara et al. (2020) firstly develop Japan's MU, following Jurado et al. (2015), by collecting as many as 67 series of Japan's macroeconomic variables in the spirit of Jurado et al. (2015): the series are all monthly and available for an extended period (since the 1970s). Also, the dataset covers a wide range of economic activities. In the current study, the dataset is slightly modified to obtain 60 series, reflecting current data availability. We find little difference between the MU estimated with this new dataset and the one with the original dataset. The new series does not qualitatively change the empirical results in Shinohara et al. (2020).

Table 1 lists the variables used for the MU for Japan. All the series except the financial variables No. 54–59 in the list are seasonally adjusted. We take the first difference, i.e., changes from the previous month, for the call rate and the 10-year government bond yield, while taking the first difference of the natural logarithm for the other variables. The dataset starts in January 1978, and the estimated MU is available from June 1979. The latest MU series is downloadable at the author's website: `https://sites.google.com/site/jnakajimaweb/mu`.

To compute the MU, we first extract common factors of the variables in the dataset. We standardize each series so that its mean is zero and its variance is one. Define $X_t = (y_{1t}, \ldots, y_{Nt})'$ as the standardized series, where N denotes the number of series. Consider a factor model

$$X_t = \Lambda^F F_t + e_t^X,$$

where F_t is the $r \times 1$ vector of the common factors; Λ^F is the $N \times r$ matrix of factor loading; and e_t^X is the $N \times 1$ vector of idiosyncratic errors. We estimate F_t by the method of static principal component analysis (PCA). We set $r = 4$ because the contribution of the fifth factor is quite small for Japan's variables. Define $\hat{F}_t = (\hat{F}_{1t}, \ldots, \hat{F}_{rt})'$ as estimated factors.

To capture a possible non-linearity in the economic agents' forecasting for macroeconomic variables, we use a squared series of the first common factor, i.e., $\hat{F}_{1t}^2$. In addition, the first common factor for the squares of the indicators, denoted by $\hat{G}_t$, is also extracted and incorporated into the model. We define $\hat{W}_t = (\hat{F}_{1t}^2, \hat{G}_t)'$.

We estimate the following linear time-series model that contains the common factors and own lags of the economic indicator as explanatory variables:

$$y_{jt} = \sum_{k=1}^{p_y} \phi_{jk} y_{j,t-k} + \sum_{k=1}^{p_F} \gamma_{jk}^F \hat{F}_{t-k} + \sum_{k=1}^{p_W} \gamma_{jk}^W \hat{W}_{t-k} + v_{jt},$$

where γ_{jk}^F and γ_{jk}^W are $1 \times r$ and 1×2 vectors, respectively. The coefficients are estimated by the least squares method, for $j = 1 \ldots, N$.

Define $\hat{v}_{jt}$ as the estimated residual of equation (3). This residual can be regarded as a proxy of one-step-ahead prediction error of y_{jt} conditional on $(X_1, \ldots, X_{t-1})$. We assume that $\hat{v}_{jt}$ follows the standard stochastic volatility (SV) model:

$$\begin{aligned} \hat{v}_{jt} &= \exp(h_{jt}/2)\varepsilon_{jt}, \\ h_{j,t+1} &= \alpha_j + \beta_j h_{jt} + \eta_{jt}, \\ \begin{pmatrix} \varepsilon_{jt} \\ \eta_{jt} \end{pmatrix} &\sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & 0 \\ 0 & \tau_j^2 \end{pmatrix} \right), \end{aligned}$$

where h_{jt} is the log-volatility, $h_{j0} = 0$ and $\eta_{j0} \sim N(0, \tau_j^2/(1 - \beta_j^2))$. We estimate the SV model using the `STOCHVOL` package in `R`, developed by Kastner and Frühwirth-Schnatter (2014). It implements the Markov chain Monte Carlo (MCMC) method with the ancillarity-sufficiency interweaving strategy. We obtain estimates using 10,000 iterations after a burn-in period of 10,000 samples. Define $\hat{h}_{jt}$, and $(\hat{\alpha}_j, \hat{\beta}_j, \hat{\tau}_j)$ as the estimated log-volatility and model parameters, respectively.

We regard the one-step-ahead expected log-volatility, $\mathrm{E}_t[\exp(h_{j,t+1})]$, as a proxy of the time-varying uncertainty in the one-step-ahead forecasting of $y_{j,t+1}$. Denote the uncertainty by $\mathcal{U}_{j,t+1}$. Using the estimates of the SV model, we compute this uncertainty measure as

$$\mathcal{U}_{j,t+1} = \exp\left(\hat{\alpha}_j + \frac{\hat{\tau}_j^2}{2} + \hat{\beta}_j \hat{h}_{jt}\right).$$

Finally, we obtain the MU by computing a simple average of the estimated uncertainty measures for all the economic indicators in the data, as

$$\mathrm{MU}_{t+1} = \frac{1}{N}\sum_{j=1}^{N}\sqrt{\mathcal{U}_{j,t+1}}.$$

It should be noted that the index is computed using the estimates of SV parameters based on the observations for the whole sample period. This approach implies that the resulting index is not an exact estimate of forecasting uncertainty conditional only on its history because the index uses future information. Also, note that the MU is not a filtered estimate of the stochastic volatility but a smoothed one. Partly due to this treatment, figures in the recent period could have significant revisions when the series is computed with an extended data sample.

Table 1: Data for the Japan's MU.

(I) Production	
1	Indices of industrial production (IIP): Total
2	IIP: Capital goods excluding transport equipment
3	IIP: Durable consumer goods
4	IIP: Non-durable consumer goods
5	IIP: Intermediate goods
6	IIP Shipments: Total
7	IIP Shipments: Capital goods excluding transport equipment
8	IIP Shipments: Durable consumer goods
9	IIP Shipments: Non-durable consumer goods
10	IIP Shipments: Intermediate goods
11	IIP Inventory: Total
12	IIP Inventory: Capital goods excluding transport equipment
13	IIP Inventory: Durable consumer goods
14	IIP Inventory: Non-durable consumer goods
15	IIP Inventory: Intermediate goods
16	Indices of tertiary industry activity
(II) Labor market	
17	The number of new job openings
18	The number of new job applications
19	The number of effective job openings
20	The number of effective job seekers
21	The number of new hires: Establishment with 30 or more employees
22	The number of total separations: Establishment with 30 or more employees
23	Total hours worked: Establishment with 30 or more employees
24	Total cash earnings: Establishment with 30 or more employees
25	The number of employment
26	The number of unemployment
(III) Trade	
27	Value of exports
28	Value of imports
29	Value of exports to the United States
30	Value of exports to China
31	Real exports
32	Real imports

Table 1: Data for the Japan's MU (cont.).

(IV) Consumption	
33	Retail sales: Total
34	Retail sales: Department stores and supermarkets
35	New car registration
36	Household spending
(V) Investment	
37	Construction starts: Floor space, private sector, non-residential
38	Construction starts: Estimated cost of construction, private sector, non-residential
39	New housing starts: Total
40	New housing starts: Owned
41	New housing starts: Rented
42	New housing starts: Built for sale
(VI) Prices	
43	Consumer price index (CPI): All items
44	CPI: All items, less fresh food
45	CPI: All items, less fresh food and energy
46	Corporate goods price index (CGPI): All items
47	Import price index (IPI): All items
48	IPI: Beverages & foods and agriculture products for food
49	IPI: Textiles
50	IPI: Metals & related products
51	IPI: Lumber & wood products and forest products
52	IPI: Petroleum, coal & natural gas
53	IPI: Chemicals & related products
(VII) Financial markets	
54	Call rate: overnight
55	Government bond yields: 10-year maturity
56	USD/JPY exchange rate
57	Nominal effective exchange rate
58	Real effective exchange rate
59	Stock price: TOPIX
60	Money supply: M2

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