Gasoline price pass-through into CPI inflation: Evidence from Structure VAR

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Abstract

We apply a Bayesian structural vector autoregression (VAR) model to estimate the impact of oil and exchange rate shocks on Japan's gasoline prices and, furthermore, Japan's gasoline price pass-through into CPI inflation. In addition to the traditional zero and sign restrictions, we adopt a Bayesian framework, which provides a broader set of credible regions. After evaluating the influence of oil supply shocks, economic activity shocks, oil-specific demand shocks, and exchange rate shocks, we found evidence that an increase in gasoline prices is associated with a positive economic activity shock and oil-specific demand shock. On the other hand, the impact of any of the above shocks was not observed on the Japanese consumer price index from the estimated results.

Keywords: Consumer price index; Structural VAR; Pass-through; Oil prices; Gasoline prices
JEL Classification: E31; F31; Q41; Q43

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1. Introduction

After the early 1990s, inflation targets became part of the monetary policy framework in many countries; these targets are set to achieve specific economic objectives, such as price stability and sustainable economic growth. As with many central banks worldwide, in 2013, the Bank of Japan (BOJ) officially adopted the inflation target of a two percent annual growth rate of the consumer price index. However, it is important to note that successfully adjusting an inflation rate in concert with the inflation target has been a persistent challenge for the BOJ. Despite their efforts, the two percent inflation rate target has never been achieved in the long term during the past nine years; see Figure 1 for the inflation rate in Japan.

Figure 1 also shows that from April 2022 until the sample data cutoff in September 2023, the inflation rate experienced 18 consecutive months of sustained growth exceeding the 2% inflation target. This persistent increase, as is well known to all, is primarily due to the impact of external shocks. In the past one or two years, a global rise in commodity prices occurred during the COVID-19 pandemic; at the same time, Russia's invasion of Ukraine has exacerbated this trend, leading to a further escalation in food and energy prices. Moreover, during this period, the continuously widening gap between domestic interest rates and foreign interest rates caused Japan's real effective exchange rate to decrease to its lowest level since the 1970s, further compounding inflationary pressures.

The Japanese economy’s inflation rate remained near zero for an extended period, but since the latter half of 2023, it has been trending around 3% year-over-year. From the perspective of expectation formation regarding the inflation rate, if this persistent rising inflation can become entrenched in people's expectations, the possibility of achieving the Bank of Japan's stable inflation target of 2% will become visible. Some studies, such as Coibion and Gorodnichenko (2015), have suggested that changes in gasoline prices explain most of the variability in inflation in the United States. This is because gasoline prices are constantly displayed at gas stations, and consumers can see them during their commute or on their way home without consciously checking them, making it one of the most memorable price changes for consumers. From the actual data trends, it seems likely that a similar relationship exists in Japan (see Figure 1), but empirical evidence regarding this relationship has not been clearly established.

During such a challenging period, it is crucial to carefully discern the current inflationary situation and ensure a definitive escape from deflation without inducing excessive inflation. Implementing policies with great caution is essential to achieve this goal. However, effective policy formulation becomes challenging when the relationship between inflation and gasoline prices remains unclear. Therefore, a quantitative analysis to elucidate this relationship is indispensable. Japan's gasoline prices have been at their highest levels since the global financial crisis, so it is necessary to ascertain how this surge will impact inflation and whether it will lead to future inflationary pressures.

On the other hand, it is believed that the factor most closely associated with gasoline price fluctuations is the variability in crude oil prices. However, many prior studies have noted that changes in crude oil prices stemming from different causes can have entirely different effects. In recent years, the different impacts of changes in the global economic cycle (economic activity factors), the production plans of the Organization of the Petroleum Exporting Countries (supply factors), and the real price of oil (oil-specific demand factors) on gasoline prices have become more apparent. Against this backdrop, when discussing changes in gasoline prices in Japan, it is necessary to consider the underlying factors simultaneously. Therefore, it is essential to emphasize the way of thinking proposed in a series of empirical studies, starting with Kilian (2008), which decomposes oil shocks into three factors: economic activity, the oil supply, and oil-specific demand shocks. Notable studies applying this concept to the Japanese economy include Fukunaga, Hirakata, and Sudo (2011), Iwaisako and Nakata (2015), and Shioji (2021). However, the existing research has focused on the direct effects of the three oil shocks on various domestic industry sectors or the impact of oil shocks on gasoline prices or inflation rates. Few studies have focused on gasoline price pass-through into CPI inflation. In addition, to our best knowledge, related existing studies have only adopted the traditional SVAR approach.

In this paper, we first investigate the impact of oil and exchange rate shocks on gasoline prices, and then we estimate the gasoline price pass-through into the CPI by adopting the SVAR model of Forbes et al. (2018). This allows us to quantify when and how much each structural shock contributes to the variation in gasoline prices in Japan and investigate the degree of correspondence between gasoline prices and the consumer price index (gasoline price pass-through)[1]. Our model consists of six variables: the consumer price index of Japan, the gasoline price of Japan, world (OECD) industrial production, world crude oil production, the crude oil spot price and the nominal effective exchange rate of the Japanese yen. In addition, we insert a methodology of a Bayesian framework (Giacomini et al., 2021) to calculate the impulse response function.

We adopt the traditional zero restrictions and sign restrictions in our model: nine zero restrictions and five sign restrictions are imposed on a structural VAR model. In

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[1] The expected range of the gasoline price pass-through are between zero percent (zero pass-through) and one hundred percent (complete pass-through).

addition to the above standard zero and sign restrictions, we also apply narrative sign episodes, which impose restrictions on the contributions of a shock on a specific period; this methodology was first introduced by Antolín-Díaz and Rubio-Ramírez (2018). Since our sample period is from January 1995 to September 2023, we consider two narrative episodes as follows: (i) September 2008 (the Great Trade Collapse) and (ii) May 2020 (the 2020 Russia–Saudi Arabia oil price war). In the first episode, world GDP decreased by 1% and world trade decreased by 10%, and this recession was across almost every country in the world. We suggest that the economic activity shock was the overwhelming contributor to a change in industrial production. In the second episode, on April 9, OPEC and Russia agreed to reduce crude oil production beginning in the following month. In the next month, crude oil production demonstrated the largest monthly depreciation (over 13%) in our sample period. We suggest that the oil supply shock is the overwhelming contributor to a change in crude oil production in that month.

As a result, we confirm the following for Japan. Not all structural shock impacts are similar; they differ when different structural shocks are in play. More specifically, this paper's most important empirical findings involve the following two points. First, not all structural shocks statistically significantly affect gasoline prices. We find a positive influence of the economic activity shock and oil-specific demand shock on gasoline prices. Second, the gasoline price pass-through driven by oil shocks and exchange rate shocks is not statistically significant.

The rest of the paper is structured as follows. The following section discusses our approach and briefly reviews the Bayesian framework for the structural VAR model. Section 3 describes the dataset and identification strategy, and Section 4 discusses the empirical results. The last section concludes the paper.

2. Empirical methodology

In this section, we briefly describe the empirical methodology of SVAR with zero restrictions and sign restrictions employed in this study. After that, we briefly describe the Bayesian framework and define our time-varying gasoline price pass-through measure.

2.1. Structural VAR model and restrictions

We follow Rubio-Ramírez, Waggoner, and Zha (2010) and Arias, Rubio-Ramírez, and Waggoner (2018) for a general structure VAR model with zero restrictions and sign restrictions. A structural VAR(p) model is represented as Equation (1).

$$y_t' A_0 = \sum_{i=1}^{p} y_{t-i}' A_{\mathrm{i}} + c + \varepsilon_{\mathrm{t}}' \qquad (1)$$

where A_0 represents an invertible $n \times n$ matrix; A_i represents autoregressive parameters in an $n \times n$ matrix of parameters for $0 \leq i \leq p$; p represents the lag length; and ***c*** represents an $1 \times n$ vector of parameters. Structural shocks in an $n \times 1$ vector form are denoted as ε_t, which is Gaussian with a mean of zero and covariance matrix I_n, and $n \times n$ is the identity matrix. The model can be expressed in reduced form as follows:

$$y_t' = \sum_{i=1}^{p} y_{t-i}' B_{\mathrm{i}} + c A_0^{-1} + u_t' \qquad (2)$$

where $B_i = A_i A_0^{-1}$, $u_t' = \varepsilon_t' A_0^{-1}$ and $E[u_t u_t'] = E[A_0^{-1\prime} \varepsilon_t \varepsilon_t' A_0^{-1}] = E[A_0^{-1\prime} A_0^{-1}] = \Sigma$. Additionally, $A_+ = \left[A_1, \ldots, A_p, c\right]$ and $B = A_+ A_0^{-1}$. The matrices B and Σ are the reduced-form parameters, whereas A_0 and A_+ are structural parameters.

Following Antolín-Díaz and Rubio-Ramírez (2018), we define impulse response functions and historical decompositions as functions of structural parameters and structural shocks. The impulse response function of the *i*-th variables to the *j*-th structural shock at horizon *h* corresponds to the matrix $L_k\left(A_0, A_+\right)$, which is defined as follows:

$$\mathbf{L}_k(A_0, A_+) = \sum_{i=1}^{k} (A_i A_0^{-1})' \mathbf{L}_{k-i}(A_0, A_+), \text{ for } 1 \leq k \leq p \qquad (3)$$

where $\mathrm{L}_0(A_0, A_+) = (A_0^{-1})'$ and $\mathrm{L}_k(A_0, A) = \sum_{i=1}^{p} (A_i A_0^{-1})' \mathrm{L}_{k-i}(A_0, A_+)$ for $p < k < \infty$.

Historical decomposition calculates the contribution of structural shocks to unexpected changes in variables. For example, the contribution of the *j*-th shock to the observed unexpected change in the *l*-th variable between periods *t* and *t*+*h* is

$$\mathbf{H}_{l,j,t,t+h}(A_0, A_+) = \sum_{k=0}^{\tau} e_{l,n}' \mathbf{L}_k(A_0, A_+) e_{j,n} e_{j,n}' \varepsilon_{t+h-k}(A_0, A_+) \qquad (4)$$

The traditional sign restrictions can be characterized by the following function, which is based on Arias, Rubio-Ramírez, and Waggoner (2018):

$$\Gamma(A_0, A_+) = (e'_{1,n} \mathrm{F}(A_0, A_+)' \mathbf{S}'_1, \ldots, e'_{n,n} \mathrm{F}(A_0, A_+)' \mathbf{S}'_n)' > 0 \tag{5}$$

For narrative restrictions, we adopt a methodology called the overwhelming driver or restriction on the historical decomposition in Antolín-Díaz and Rubio-Ramírez (2018)[2]. This imposes a sign on the *j*-th shock on the date *h*. For example, for a shock restriction, the contribution of the *j*-th shock to the *l*th variable on the date *h* is larger in absolute terms than the sum of the contributions of all other shocks.

$$\left|\mathrm{H}_{l,j,t,t+h}(A_0, A_+)\right| > \sum_{j' \neq j} \left\{\left|\mathrm{H}_{l,j',t,t+h}(A_0, A_+)\right|\right\} \tag{6}$$

Finally, the structural parameters of the SVAR model are collectively identified by extracting a set of reduced parameters from the posterior distribution, plotting the orthogonal matrix, recovering the structural parameters, and checking whether they satisfy the identification restrictions of zero, traditional signs, and narrative signs.

2.2. Bayesian SVAR framework

As argued in the previous section, traditional SVAR uses the median to represent impulse responses. This can cause the following problems: (1) in the estimation of SVARs, once a structural parameter satisfying the constraints imposed for identification is obtained through repeated random draws from the prior distribution, one impulse response function corresponding to that structural parameter is obtained; (2) a sufficiently large number of draws satisfying the constraints (for example, 1,000) are obtained to represent the posterior distribution; however, as each impulse response function may intersect with each other, it is not possible to consider a specific draw (satisfying the constraints) as the median; and (3) it has been shown in various empirical studies that impulse responses resembling the median do not emerge from any particular draw of that study, indicating that the likelihood of such impulse responses occurring in the real economy is extremely low. This is the same problem as the median; there are also issues with percentile selection. Because percentiles for each period after the shock (t = 1, 2, 3, etc.) are chosen, no impulse response line connects each percentile (e.g., the 2.5th percentile). From the set of 1,000 impulse responses extracted satisfying the constraints,

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[2] See Antolín-Díaz and Rubio-Ramírez (2018) for a summary of the narrative sign restrictions.

it is possible that a specific impulse response, when removed, may extend beyond the confidence interval at some time point after the shock. As a solution to the above problem, Baumeister and Hamilton (2020) propose that reporting the median and 68% interval of the set of retained draws is not justified. Instead, the researcher should report the full set of all retained draws.

We adopt the full set of all retained draws (100% confidence interval) proposed by Baumeister and Hamilton (2020), that is to calculate all the impulse responses that can satisfy the restrictions. In terms of results, the full set of all retained draws provides a broader set of draws, so any research results are less likely to reject the null hypothesis. Therefore, the effects are more likely to be not statistically significant. On the other hand, if any effects are statistically significant using the full set of all retained draws, the results can be expected to be more credible.

In this paper, we follow Giacomini and Kitagawa (2021) and Giacomini et al. (2021) to compute the set of impulse responses. As Baumeister and Hamilton (2020) suggested, all draws of impulse responses are shown in the results[3]. Specifically, Giacomini and Kitagawa (2021) added another step after obtaining a draw from the posterior distribution of the reduced-form parameter, ϕ, which satisfies zero and has traditional sign restrictions.[4]

We will describe the Bayesian framework below in more detail. As the first step, we obtain a set of reduced-form parameters, $\tilde{\phi} = (\tilde{\mathbf{B}}, \tilde{\Sigma})$, generated from the Wishart-inverse distribution with the estimated parameters, $\hat{\phi} = (\hat{\mathbf{B}}, \hat{\Sigma})$. The structural parameter $(\tilde{A}_0^{-1})$ is constructed by multiplying $Chol(\tilde{\Sigma})$, the Cholesky decomposition of $\tilde{\Sigma}$, and an orthonormal matrix $\tilde{Q}$, the q matrix of the QR decomposition of an n-dimensional matrix drawn from the multinormal distribution.[5] Note that zero restrictions are imposed at this stage for the construction of $\tilde{Q}$.

Then, as the second step, impulse response functions, $\mathbf{L}_k(\tilde{A}_0, \tilde{A}_+)$, as in Equation (3), are calculated and checked for whether traditional sign restrictions and narrative sign restrictions are satisfied. Retaining $Chol(\tilde{\Sigma})$, we continue to replace $\tilde{Q}$ with alternative orthonormal matrices for the maximum of L times until all restrictions are satisfied.

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[3] Inoue and Kilian (2020) argued that Baumeister and Hamilton (2015, 2020)'s criticism is too strong and overstated. They concluded that conventional SVAR remains appropriate for most studies. But this is not to negate the usefulness of Giacomini and Kitagawa (2021) and Giacomini et al. (2021).

[4] This is step 3' of Algorithm 2 in Giacomini and Kitagawa (2021).

[5] In Giacomini and Kitagawa (2021), the linear projection method (Step 2.1 in Algorithm 1) is used and the QR decomposition method is provided as an alternative.

We set the parameters for the Bayesian SVAR estimation as follows. Based on the Akaike information criterion, we chose the number of lags to be six. The number of draws from the posterior of $\tilde{\phi} = (\tilde{\mathbf{B}}, \tilde{\Sigma})$ that satisfies the restrictions is 1,000. The number of draws for the alternative orthonormal matrices to check whether the restrictions are satisfied is 10000. The number of alternatives $\tilde{Q}$ for a fixed $Chol(\tilde{\Sigma})$, is set to be $\tilde{K} = 1000$.

2.3. Gasoline price pass-through definition

One of the purposes of this paper is to understand the time-varying changes in the gasoline price pass-through to the consumer price index, which depends on the underlying shocks. After obtaining impulse responses of the gasoline price and consumer price index from individual structural shocks, we can define the shock-specific gasoline price pass-through as the ratio of the cumulative changes in the consumer price index to the cumulative changes in the gasoline price to the corresponding structural shock. Using the results of the VAR model, the gasoline price pass-through is defined as the ratio of the impulse response of the consumer price index to each shock and the impulse response of the gasoline price to each shock. $IR_p(t,j) = e'_{p,n} L_t\left(A_0, A_+\right) e_{j.n}$ is the impulse response of variable p, at the t-th month after the j-th structural shock. The gasoline price pass-through (GPPT) to the consumer price index evaluated at the τ-th month after the j-th structural shock is defined as follows[6]:

$$GPPT(\tau, j) \equiv \frac{\sum_{t=0}^{\tau} IR_p(t,j)}{\sum_{t=0}^{\tau} IR_{gp}(t,j)} \tag{7}$$

Therefore, the gasoline price pass-through measured via this approach is time-varying and also changes on the basis of the corresponding shock. This allows us to identify whether the gasoline price pass-through changes in response to corresponding shocks and explore the economic implications of this pass-through change. This pass-through approach was also adopted by Forbes et al. (2018) and Yoshida et al. (2022) to explain the exchange rate pass-through's time-varying change.

3. Data and Restrictions of the SVAR Model

3.1. Data

Our model contains six variables: economic activity, proxied by world industrial

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[6] The gasoline price pass-through is defined between -1 and 1 by additional restrictions.

production growth according to OECD statistics (economic activity shock); the growth rate of global oil production (oil supply shock) and the real price of crude oil (oil-specific demand shock), according to the Energy Information Administration; and the consumption tax-adjusted consumer price index and gasoline price, calculated by the Ministry of Internal Affairs and Communications. We estimate the SVAR model described above using monthly data for the period from 1995M1 through 2023M9.

3.2. SVAR model

Our SVAR model is defined on the basis of Equation (1), which is applied to the variables[7] and can be expressed as follows:

$$\left[\,\Delta CPI_t \;\; \Delta\, GP_t \;\; \Delta OP_t \;\; \Delta EA_t \;\; \Delta OSD_t \;\; \Delta neer_t\,\right] A_0 = \sum_{i=1}^{6}\left[\,\Delta CPI_{t-i} \;\; \Delta\, GP_{t-i} \;\; \Delta OP_{t-i} \;\; \Delta EA_{t-i} \;\; \Delta OSD_{t-i} \;\; \Delta neer_{t-i}\,\right] A_i + \varepsilon_t \tag{8}$$

where $\Delta\mathrm{CPI}$ is the inflation rate, $\Delta\mathrm{GP}$ is the percentage of change in Japan's gasoline price, $\Delta\,\mathrm{OP}$ is the growth rate of global oil production, $\Delta\,\mathrm{EA}$ is the world (OECD) industrial production growth, $\Delta\,\mathrm{OSD}$ is the percentage of change in the real price of crude oil, and $\Delta\mathrm{neer}$ is the rate of change in the nominal exchange rate[8]. As mentioned above, to identify structural shocks, we put a number of zero, sign, and narrative sign restrictions on the impulse responses of the endogenous variables to the corresponding structural shocks, which is briefly described in the following subsections.

3.3. Zero and sign restrictions

Table 1 presents the short-run zero, long-run zero, and sign restrictions. These restrictions are consistent with those of some previous studies. The top panel represents the short-run zero and traditional sign restrictions. First, following Kilian et al. (2009), we use three short-run zero restrictions to show the relationships among the three types of oil shocks. These studies assume that oil producers are free to respond to both lagged values of oil prices and global economic activity, but considering the adjusted costs and uncertainty, oil production will not respond to economic activity and oil-specific demand shocks in the same month. Moreover, an oil-specific demand shock will not influence

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[7] Therefore, the beginning of the sample starts from the seventh quarter of 1995 in the regression.

[8] We also tried to use another data definition of crude oil shocks that is closer to that of Killian (2008): except for world industrial production and the growth rate of global oil production, all data are natural logarithm series (proceed by the Hodrick-Prescott filter). The results from using this dataset are almost consistent with our main conclusions.

global economic activity in the same month.

Second, the following sign restrictions have been devised. A positive nominal gasoline price shock is assumed to increase the real price of gasoline, which in turn affects the consumer price index in the same period (Kilian and Zhou, 2022a). An exchange rate shock, which is known as Japanese yen appreciation, has a negative effect on both gasoline prices and consumer prices in Japan.

The bottom panel represents our six long-run zero restrictions; we assume that shocks originating within a country's exchange rate do not affect the variables related to the international crude oil market (Kilian and Zhou, 2022b). Furthermore, gasoline prices in Japan are the cause of oil shocks, so there will be no adverse impacts.

3.4. Narrative sign restrictions

In addition to the traditional zero and sign restrictions, we select two crucial episodes in which the effect of a specific structural shock clearly constitutes the overwhelming contribution to a change in one of the endogenous variables from both international and domestic perspectives during the sample period. These two episodes are shown as vertical lines in Figure 3. (i) The first episode is the Great Trade Collapse in September 2008. Worldwide, trade experienced a sudden and sharp fall. The narrative restriction for this episode is as follows: the negative economic activity shock deteriorated world industrial production, and its contribution was overwhelming. (ii) The second episode is the 2020 Russia–Saudi Arabia oil price war. On April 9, OPEC and Russia agreed to reduce crude oil production beginning in the following month. This reduction in oil production was also the most significant during our entire sample period. We impose a narrative restriction in which the oil supply shock decreases oil production, and its contribution is overwhelming.

4. Empirical Results

In this section, we turn to the empirical analysis results. The main sample period spans from January 1995 to September 2023. Figure 4 shows the cumulative impulse response functions of the gasoline price, and Figure 5 represents the gasoline price pass-through which is calculated as the ratio of the consumer price index's accumulated impulse response to the gasoline price's accumulated impulse response with respect to corresponding shocks, as defined by Equation (7).

The horizontal axis represents the number of months after the shock. The red dashed curves show the impulse response functions of all the 1000 draws. We also report the conventional 68-percent credible regions, which are shown by the blue solid curve. Similar to the conventional SVAR methodology, the 68-percent credible regions are computed from the maximum and minimum values of 1000 draws.

4.1. Cumulative impulse responses functions of the gasoline price

Figure 4 represents the cumulative impulse responses of the gasoline price with respect to each structural shock from January 1995 to September 2023. We can classify these four shocks into three groups. The first group of shocks does not affect Japan's gasoline price movement. The null hypothesis cannot be rejected for the exchange rate shock. This result indicates that Japanese gasoline price was insulated from exchange rate movements. The effects of the second group of shocks depend on the statistical methods used. With conventional confidence intervals, positive oil supply shocks persistently decrease the gasoline price, these shocks are statistically significant from the 9th to the 60th month. Not surprisingly, this means that the reduction of crude oil production will lead to higher gasoline prices. However, this influence is not statistically significant from zero according to the full set of all retained draws. This is where the approach of Baumeister and Hamilton (2020) play a vital role in conducting correct statistical inference.

The third group shocks affect Japan's gasoline price movement in both conventional confidence intervals and the Bayesian approach. Positive economic activity shocks and oil-specific demand shocks persistently increase gasoline prices in Japan. And the conventional confidence intervals are well above zero. According to the full set of all retained draws, except for extremely few draws, all 1000 draws' impulse responses are persistently positive.[9] Moreover, the full set of all retained draws shows the lag of economic activity shocks, they are not statistically significant except after seven months. These effects on the gasoline prices in Japan are consistent with some previous studies, such as Shioji (2021), Yilmazkuday (2021) and Yoshizaki and Haomori (2014).

Significantly, not all four kinds of shocks are associated with the same corresponding movements in the gasoline prices. Each structural shock induces different signs of gasoline price changes. From comparing the differences between the conventional credible region and the full set of all retained draws, we find that, unlike economic activity shocks and oil-specific demand shocks, the conclusion of some studies previously believed that supply shock would cause oil prices to decrease is proved to depend on the statistical methods used.

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[9] Seven draws are always below zero for oil-specific demand shocks, and 15 draws are always below zero for economic activity shocks after the 7th month.

4.2. Gasoline price pass-through

Figure 5 represents the impulse responses of the cumulative gasoline price pass-throughs with respect to the four structural shocks. Overall, zero gasoline price pass-through cannot be rejected for the oil supply, economic activity, oil-specific demand and exchange rate shock. All four shocks do not affect Japan's inflation.

We can still see subtle differences between the two statistical methods. The gasoline price pass-through induced by economic activity shocks is statistically significant from the 2nd month and the 60th month with respect to the conventional credible region. This means that an increase in the consumer price index is associated with an increase in gasoline price when Japan is affected by a positive economic activity shock. However, they are not statistically significant with respect to the full set of all retained draws.

4.3. Robustness check

First, the COVID-19 pandemic in 2020 and 2021 lowered economic activity globally by shutting down service consumption locally and internationally. Although we imposed the 2020 Russia–Saudi Arabia oil price war in May 2020 in the main analysis to indicate the overwhelming influence of the oil supply shock, there may also be a considerable influence from other exogenous shocks during this period. To curb the rise in fuel oil prices due to the influence of COVID-19, the Japanese government introduced a gasoline subsidy policy beginning in January 2022. Specifically, if the national average gasoline price exceeds 170 yen per liter, subsidies will be provided to fuel oil wholesalers up to a maximum of 5 yen per liter. This policy continued until the end of our sample period. Considering the impact of the gasoline subsidy policy, we also estimated the same SVAR model with the sample period ending in December 2021, just before the policy implementation in Japan.

From Figure 6, we have not found any significant changes in conventional confidence intervals compared to Figure 4. However, if we focus on the full set of all retained draws, the economic activity shock (the top-right figure) results can be found to have changed a lot. The draws below zero have increased significantly, the statistical significance of the economic activity shock disappears. At the same time, Figure 7 shows that the significance of gasoline price pass-through induced by economic activity shock (the top-right figure) with respect to the conventional credible region also disappears. This may mean that even with the gasoline subsidy policy in place, the economic activity shocks still positively impacted gasoline prices in Japan during the subsidy period.

Second, in the main analysis, we chose two episodes, namely, the Great Trade Collapse in September 2008 and the beginning of the 2020 Russia–Saudi Arabia oil price war in May 2020, to impose narrative sign restrictions on the structural VAR model. How does the imposition of these narrative sign restrictions affect the estimation results? To quantify the contribution of these narrative sign restrictions, we obtained full set of all retained draws results without narrative sign restrictions while maintaining everything else intact.

In Appendix Figures A1 and A2, both the impulse response function and gasoline price pass-through are almost consistent with the main analysis. The only notable changes are similar to the first robustness check: the gasoline price pass-through induced by economic activity shock (the top-right figure of Figures A2) with respect to the conventional credible region is no longer significant.

4.4. Discussions

Thus far, we find that an increase in the gasoline price is only associated with positive economic activity shock and oil-specific demand shock. We have not found evidence that oil and exchange rate shocks impact inflation in Japan. However, are these results of shocks peculiar to Japan? Related to our aims, some studies have examined the relationship between the oil price and Japan's inflation. Two other studies examined whether the oil price drives inflation: Yoshizaki and Haomori (2014) and Renou-Maissant (2019).

Yoshizaki and Haomori (2014) applied the SVAR model to investigate the dynamic effects of changes in the oil price on the CPI in the United States and Japan from December 1974 to December 2010. They found that the transmission mechanisms of higher oil prices differ considerably between the United States and Japan. More specifically, unlike the United States, which is strongly affected by aggregate demand shocks, Japan is affected mainly by oil demand shocks. Unanticipated oil demand shocks lead to a temporary increase in Japan's CPI, and the amount of increase is relatively greater than that in the United States. This conclusion is close to our finding that an increase in the gasoline price is only associated with a positive oil demand shock.

Renou-Maissant (2019) investigated the effects of oil price changes on inflation over the period 1991–2016 for eight industrial countries: the United States, Canada, Japan, Australia, Germany, France, Italy, and the UK. They noted that for these countries, oil prices play a significant role in inflation dynamics over the period in all countries. However, they also mentioned that the inflationary effect of oil prices varies across countries and that Japan's effect is the lowest among the eight countries. The time-varying paths of the oil pass-through coefficient indicate that this parameter has started to decline in Japan since approximately 2009. Considering the difference in the sample period, this may be one of the reasons why the response of our CPI to oil shocks is different from that of Yoshizaki and Haomori (2014).

In addition, Antonio and Luis (2022) analyzed oil price fluctuations and headline inflation, focusing on the Euro-area, the UK, and Japan. As a result, unlike in other countries where the oil price has been confirmed to have a significant effect on inflation, the role of the exchange rate in Japan's oil price pass-through is lower and insignificant.

5. Conclusion

Despite the continuous effort of quantitative easing by the Bank of Japan, the two percent inflation rate target has never been achieved in the long term during the past nine years. During the 18 months prior to the end of our sample period, Japan's inflation growth was approximately 3% due to the influence of external shocks such as the COVID-19 pandemic and Russia's invasion of Ukraine. Nevertheless, it remains uncertain whether this indicates a turning point for the Bank of Japan to achieve the long-term 2% inflation rate target.

In this paper, we first investigate the impact of oil and exchange rate shocks on Japan’s CPI and gasoline prices and then estimate the gasoline price pass-through to the CPI in Japan. As a result, we only find a positive influence of oil-specific demand shocks on the price of gasoline. For Japan’s CPI, zero gasoline price pass-through cannot be rejected for the gasoline price, exchange rate, oil supply, economic activity, and oil-specific demand shocks. As several previous studies have noted, we have confirmed the particularity of the relationship between Japan’s CPI and crude oil shocks. This can be partially explained by the lower oil intensity of Japan and the higher proportion of taxes in oil prices. The higher the fuel tax wedge is, the smaller the proportional impact on the prices of a given rise in oil prices. In addition, our results show that the gasoline price subsidy policy in recent years has effectively curbed the possibility of gasoline price changes affecting all items of the consumer price index. In addition, our results show that the gasoline price subsidy policy in recent years has effectively curbed the possibility of gasoline price changes affecting all items of the consumer price index. However, an economic activity shock still positively impacted gasoline prices in Japan during the subsidy period.

As proposed by Cologni and Manera (2008), for some countries (such as the U.S.), a significant part of the effects of the oil price shock are due to monetary policy reactions. For Japan, the path of oil prices is lower under the assumption of no monetary response. This may reflect the current situation in Japan. For the continued implementation of a quantitative easing monetary policy, it is difficult to implement effective policy adjustments to address exogenous crude oil shocks. If a sustained negative crude oil-specific demand shock occurs, it is likely to have an effect on Japan's gasoline prices and thus on the CPI. The BOJ should continue to monitor oil price fluctuations closely, especially when they are prolonged over time.

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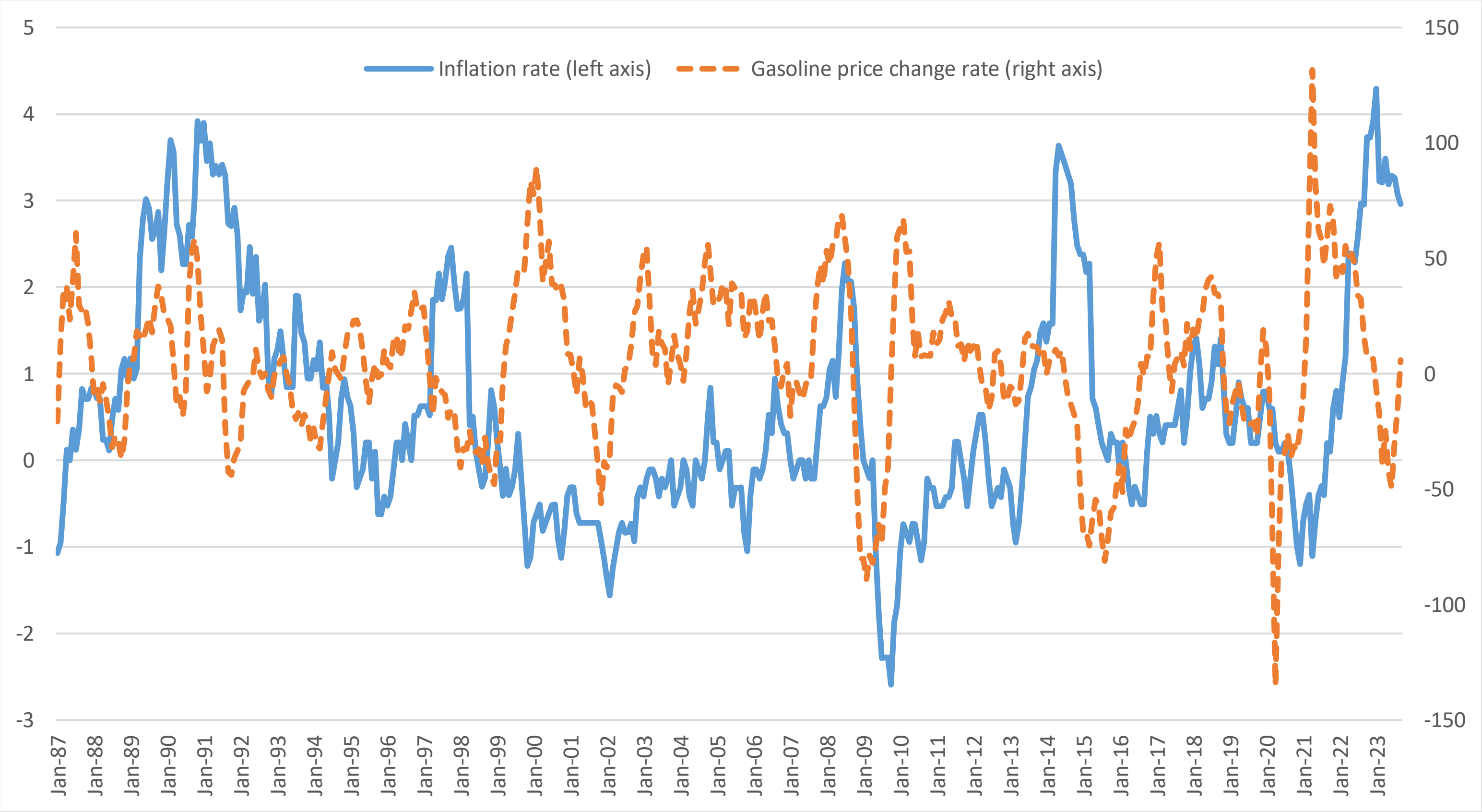
Table 1. Identification restrictions

	JPN demand shock	JPN gasoline price shock	Oil supply shock	Economic activity shock	Oil-specific demand shock	Exchange rate shock
Short-run restrictions						
JPN CPI	+	+				**-**
JPN gasoline price		+				**-**
Oil production				**0**	**0**	
Economic activity					**0**	
Oil price						
Nominal effective exchange rate						
Long-run restrictions						
JPN CPI						
JPN gasoline price						
Oil production	**0**	**0**				**0**
Economic activity	**0**	**0**				**0**
Oil price						
Nominal effective exchange rate						

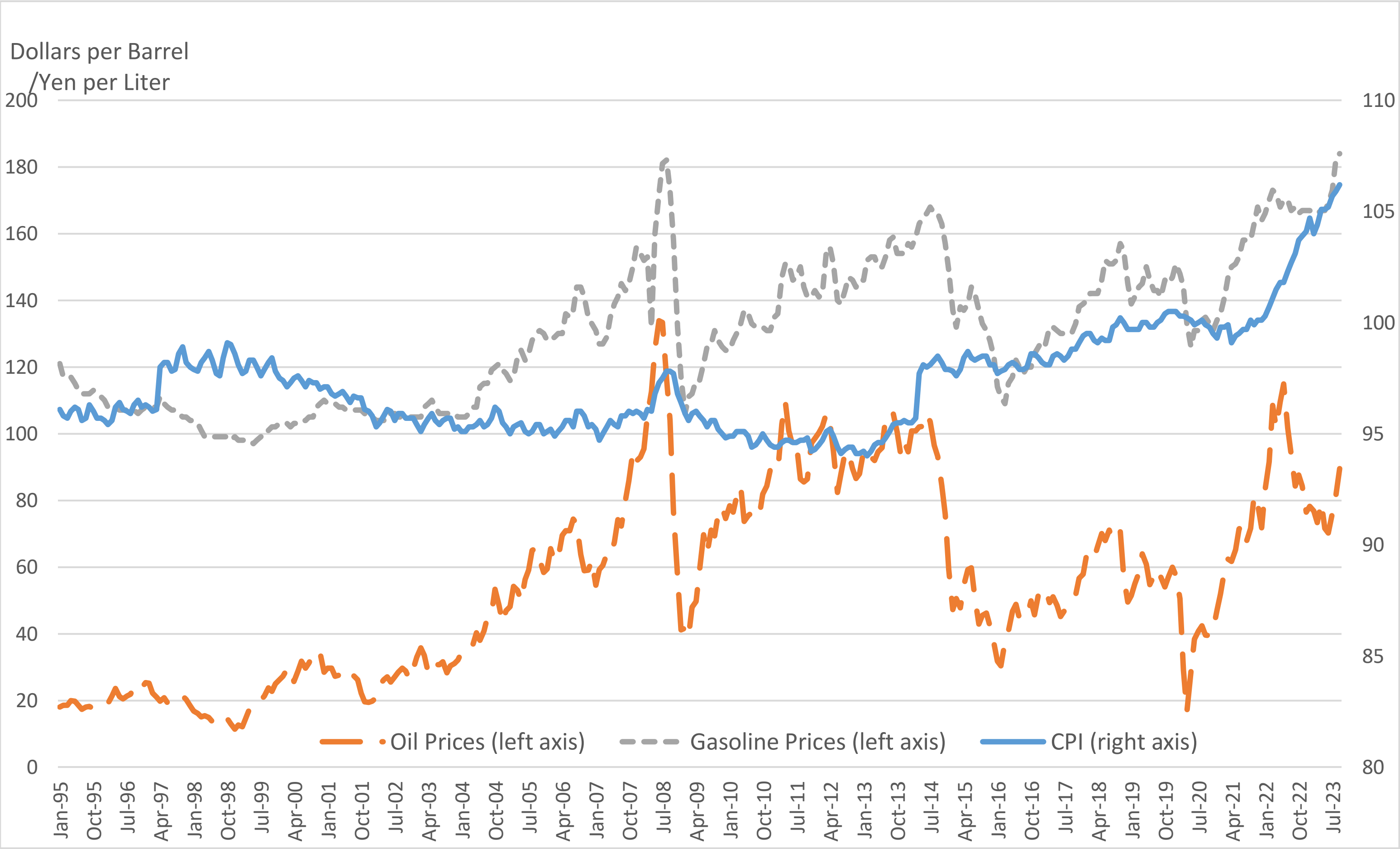
Note: A ‘0’, ‘+’, or ‘-‘ sign indicates that the impulse response of the variable listed in the row to the shock in the column is zero, positive, or negative, respectively, in the month in which the shock occurs and in the following month.

Figure 1. The inflation rate and gasoline price change rate of Japan, 1987M1–20223M9.



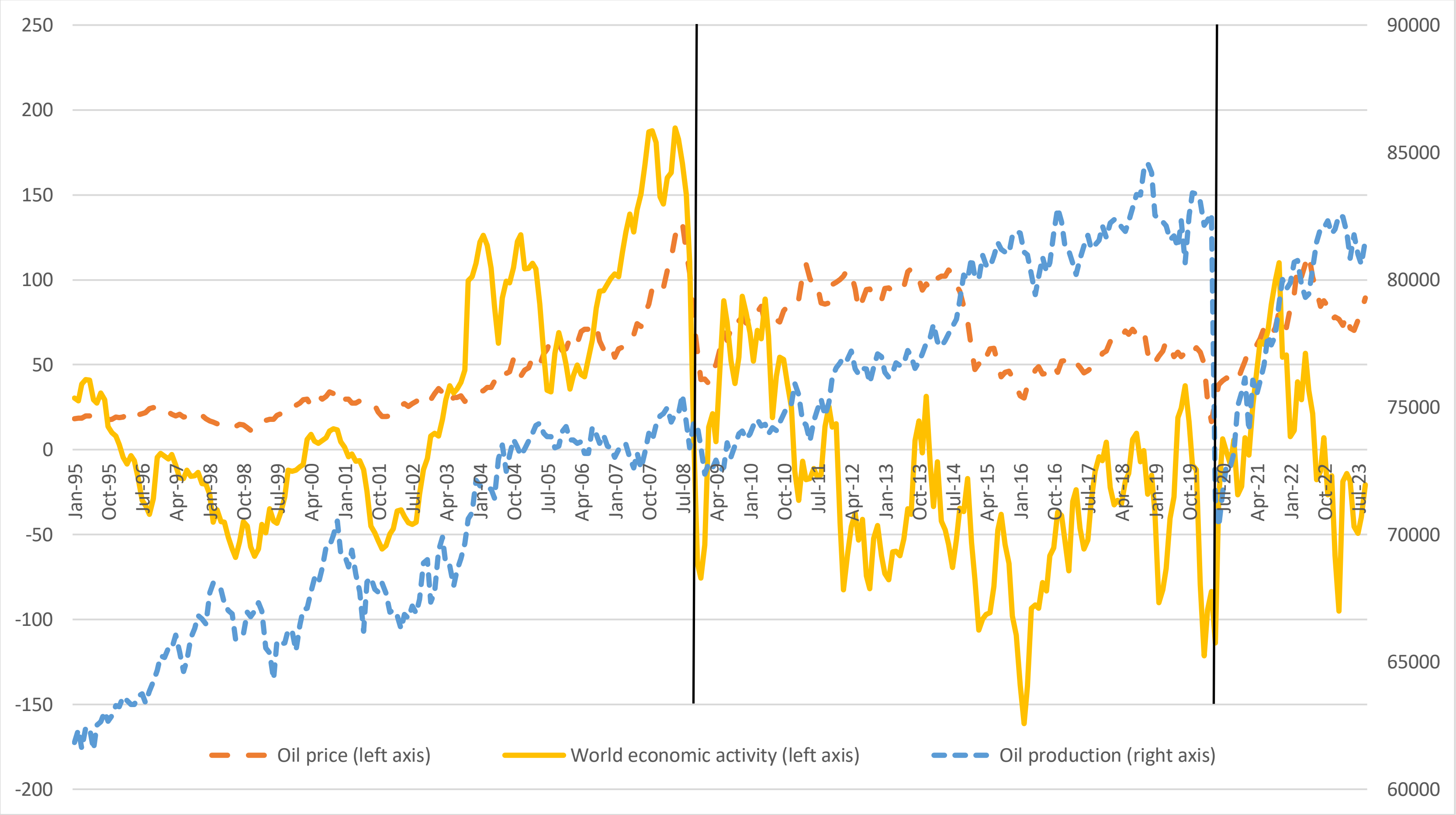
Notes: The inflation rate is the log difference of the consumer price index adjusted for consumption tax, and the gasoline price change rate is the log difference of the gasoline prices in the Japanese market, measured for the current month's change from the same month in the previous year.

Figure 2. The oil, gasoline, and consumer prices of Japan, 1995M1–20223M9.



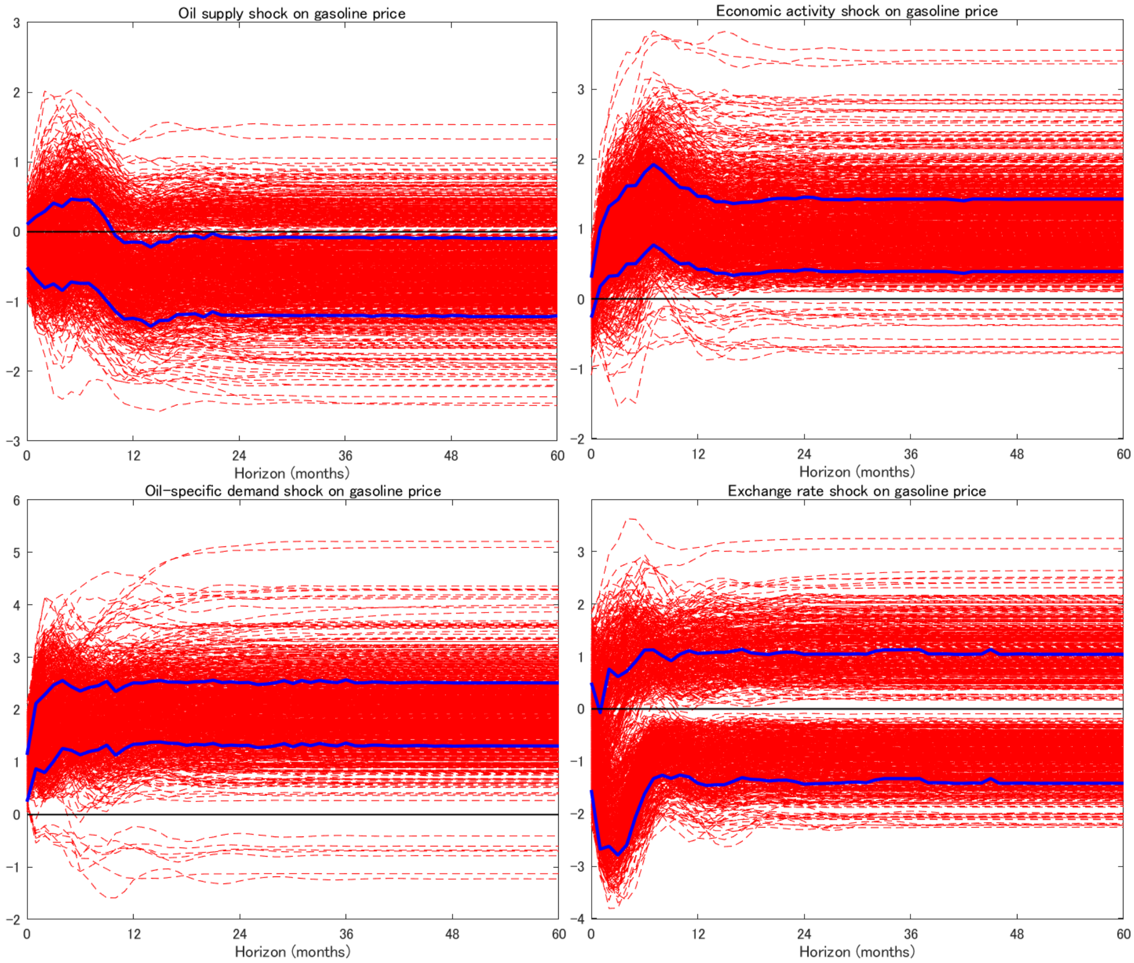
Notes: The oil price is the spot price of crude oil (dollars per barrel). Gasoline prices are the value of retail prices. The CPI is the consumer price index adjusted for the consumption tax.

Figure 3. The oil production, world economic activity, and oil price, 1995M1–20223M9.



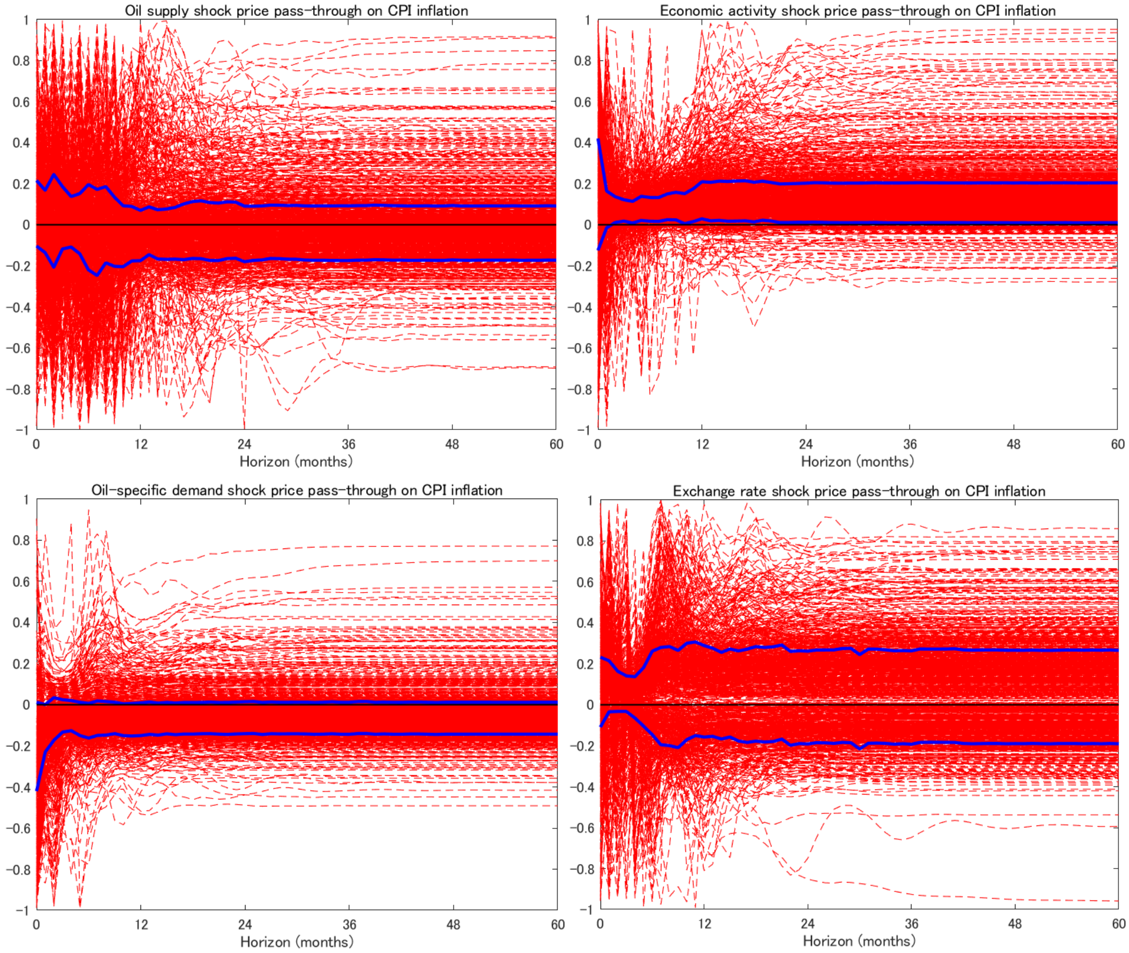
Notes: The oil price is the spot price of crude oil (dollars per barrel). World economic activity is the index of global economic activity. Oil production is the worldwide crude oil production (Mb/d).

Figure 4. Cumulative impulse response functions (IRF) for the gasoline price.



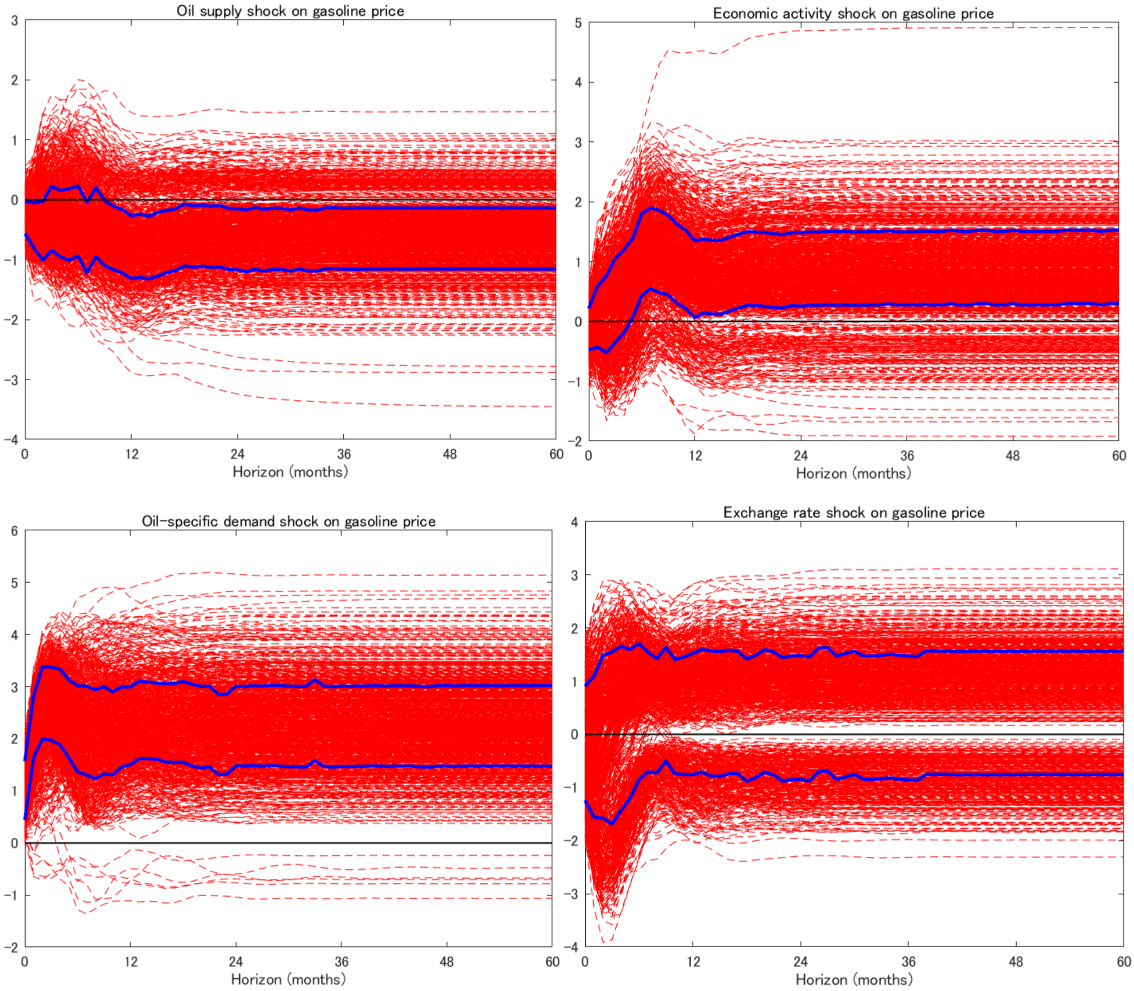
Notes: The red dashed curves show the impulse response functions of all the 1000 draws that satisfied the identification restriction. The blue solid line shows the conventional 68-percent credible regions. The data sample is from 1995M1 to 2023M9.

Figure 5. Gasoline price pass-through on CPI.



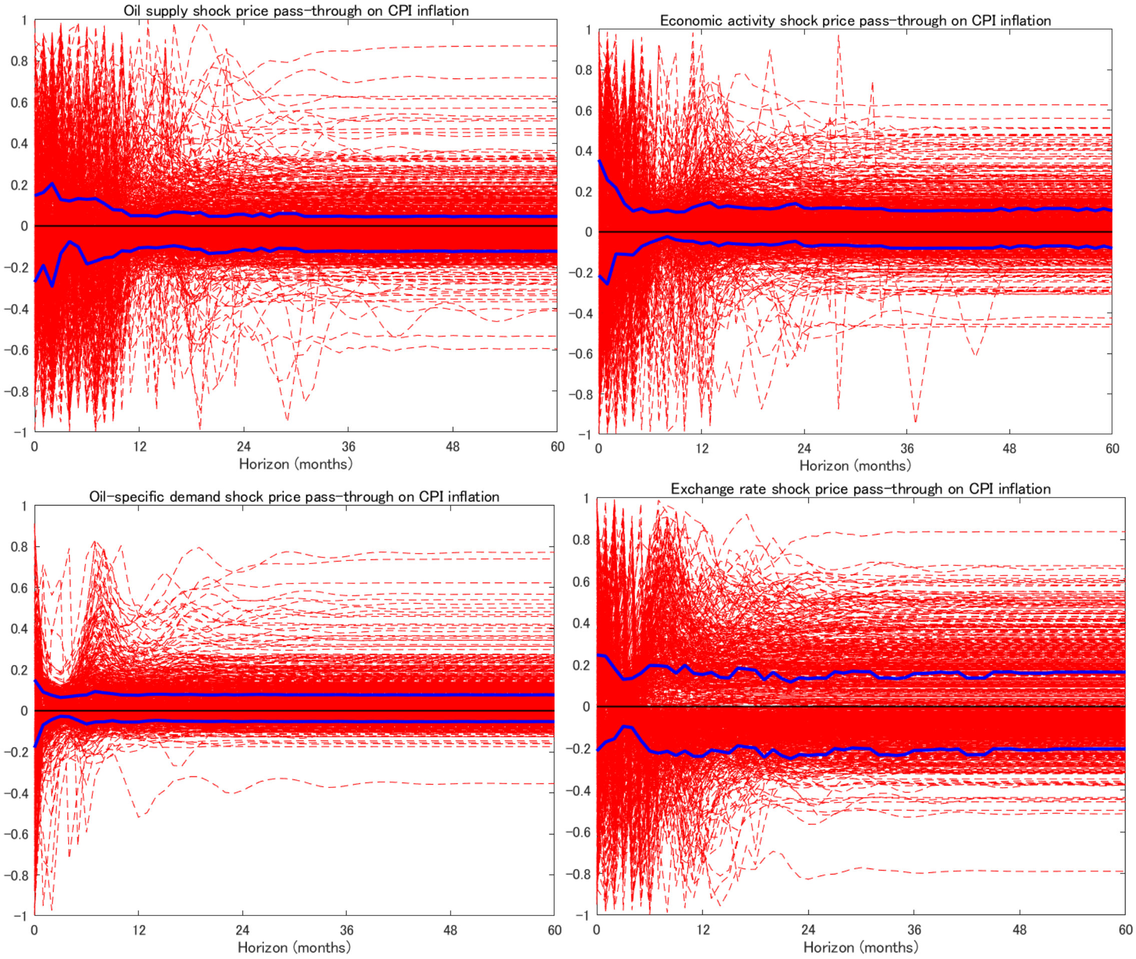
Notes: The red dashed curves show the impulse response functions of all the 1000 draws that satisfied the identification restriction. The blue solid line shows the conventional 68-percent credible regions. The data sample is from 1995M1 to 2023M9.

Figure 6. Comparison with the IRF (before gasoline subsidy policy).



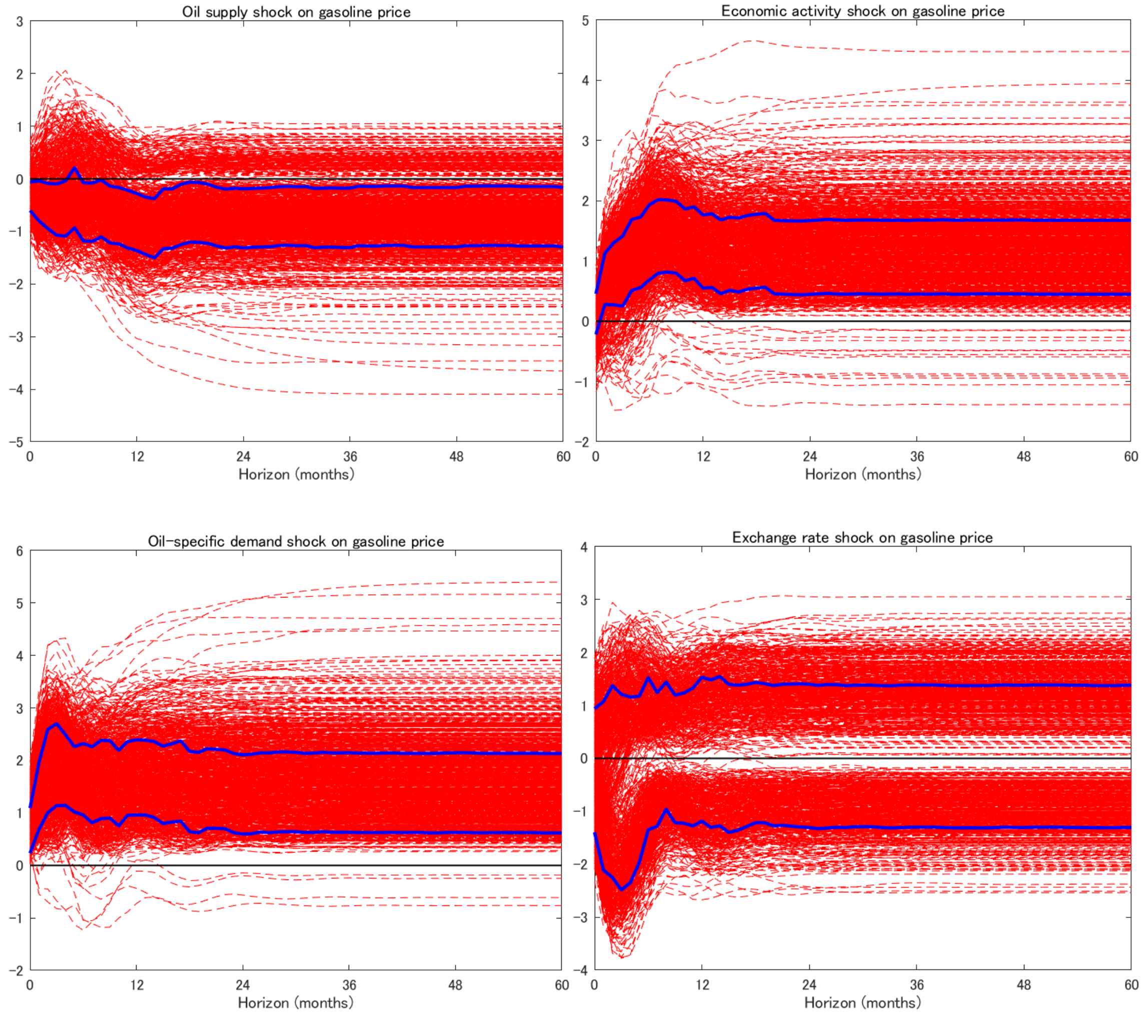
Notes: The red dashed curves show the impulse response functions of all the 1000 draws that satisfied the identification restriction. The blue solid line shows the conventional 68-percent credible regions. The data sample is from 1995M1 to 2021M12.

Figure 7. Comparison with the GPPT on CPI (before gasoline subsidy policy).



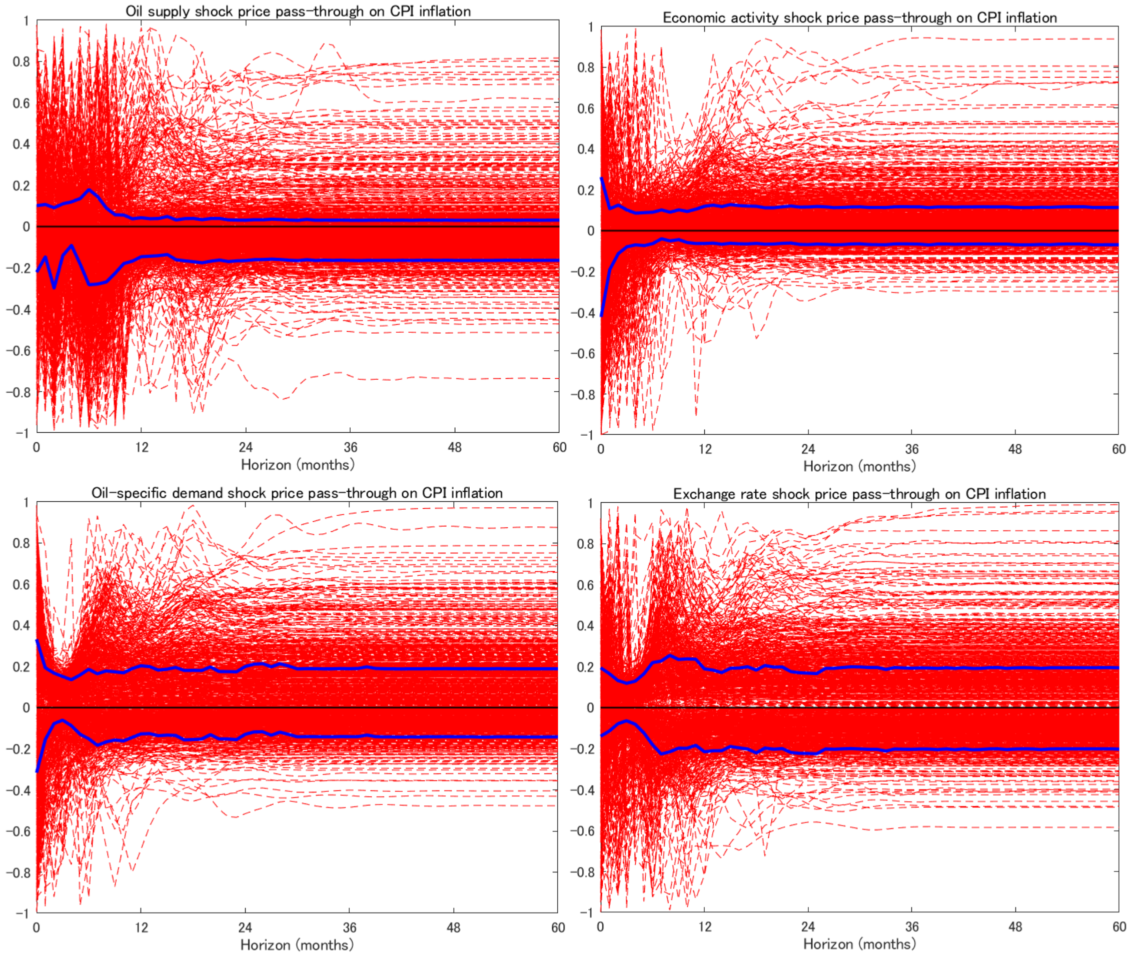
Notes: The red dashed curves show the impulse response functions of all the 1000 draws that satisfied the identification restriction. The blue solid line shows the conventional 68-percent credible regions. The data sample is from 1995M1 to 2021M12.

(Appendix) Figure A1. Cumulated impulse response functions for the gasoline price, nonnarrative sign restrictions.



Notes: The red dashed curves show the impulse response functions of all the 1000 draws that satisfied the identification restriction. The blue solid line shows the conventional 68-percent credible regions. The data sample is from 1995M1 to 2023M9.

(Appendix) Figure A2. Gasoline price pass-through to the CPI, nonnarrative sign restrictions.



Notes: The red dashed curves show the impulse response functions of all the 1000 draws that satisfied the identification restriction. The blue solid line shows the conventional 68-percent credible regions. The data sample is from 1995M1 to 2023M9.