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

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Abstract

We apply a robust Bayesian structural VAR model to estimate the impact of oil and exchange rate shock on Japan's CPI and gasoline prices and, furthermore, Japan's gasoline price pass-through. In addition to the traditional zero and sign restrictions, we adopt a robust multi-prior Bayesian framework, which provides a broader set of credible regions. After evaluating the influence of oil supply shock, economic activity shock, oil demand shock, and exchange rate shock, we found evidence that an increase in gasoline prices is associated with a positive oil demand shock. On the other hand, we have not observed the impact of any of the above shocks 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, the Bank of Japan (BOJ) officially adopted 2013 the inflation targeting of a two percent annual growth rate of the consumer price index. However, it's 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's 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, the 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 and foreign interest rates caused Japan's real effective exchange rate to drop to its lowest level since the 1970s, further compounding the 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-on-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 targeted stable 2% inflation will become visible.

Some research, such as Coibion and Gorodnichenko (2015), has 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 grasp them without consciously checking, such as during their commute or on their way home, 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. To achieve that, implementing policies with great caution is essential. However, effective policy formulation becomes challenging when the relationship between inflation formation and gasoline prices remains unclear. Quantitative analysis to elucidate this relationship is therefore indispensable. As Japan's gasoline prices are approaching their highest levels since the global financial crisis, it is necessary to ascertain how this surge in gasoline prices 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 pointed out 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 (demand factors) on gasoline prices have become more obvious. 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, oil supply, and oil 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, existing research is basically 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. There have been few studies focusing on gasoline price pass-through into CPI inflation.

In this paper, we first investigate the impact of oil and exchange rate shock on Japan’s CPI and gasoline prices, and then we estimate the gasoline price pass-through into CPI by adopting the SVAR model of Forbes et al. (2018). In this way, we can examine when and how much each gasoline price appreciation episode contributed to raising the consumer price index in Japan. Our model consists of six variables: the consumer price index of Japan, the gasoline price of Japan, the nominal effective exchange rate of the Japanese yen, the world crude oil production, World (OECD) Industrial production, and crude oil spot price. In addition, we insert a methodology of robust multi-prior Bayesian framework (Giacomini et al., 2021) into the Forbes model to calculate the gasoline price path-through.

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 addition to the above standard zero and sign restrictions, we also apply narrative sign episodes, which impose restrictions on contributions of a shock on a specific period; this methodology is introduced first by Antolín-Díaz and Rubio-Ramírez (2018). Since our sample period is from January 1995 to September 2023, we considered 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 dropped by 1% and world trade dropped by 10%, and this recession was across almost every country in the world. We impose that the economic activity shock was the overwhelming contributor to a change in OECD industrial production. In the second episode, on 9 April, OPEC and Russia agreed to reduce the crude oil production from the following month. In the next month, the crude oil production demonstrated the largest monthly depreciation (over 13%) in our sample period. We impose that the oil production shock is the overwhelming contributor to a change in the crude oil production in that month.

In terms of econometric methodology, although the traditional SAVR approach are widely accepted by previous studies, this approach is criticized in some recent studies (For example, the pointwise median impulse response function does not correspond to any impulse responses in the identified set)[1]. For the above reasons, instead of the traditional SVAR approach, we adopt a relatively new approach in this paper, which is called Robust Bayesian SVAR, introduced by Giacomini, Kitagawa, and Read (2021, 2022) and Giacomini and Kitagawa (2021). As an alternative to the conventional SVAR estimates, in the GKR approach, alternative Q matrices are applied to the draws of estimates that satisfy zero, traditional sign, and narrative sign restrictions to compute the credible region[2].

As a result, we only find a positive influence of oil demand shock to gasoline price. For Japan's CPI, the zero gasoline price pass-through cannot be rejected for gasoline price, exchange rate, oil supply, economic activity, and oil demand shocks. As some previous studies have pointed out, we have also confirmed the particularity of the relationship between Japan's CPI and crude oil shocks.

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.

2. Empirical methodology

In this section, we briefly describe the empirical methodology of SVAR with

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[1] See Baumeister and Hamilton (2015, 2020) and Inoue and Kilian (2013)

[2] See Giacomini, Kitagawa, and Read (2021, 2022) and Giacomini and Kitagawa (2021)

zero restrictions and sign restrictions employed in this study. After that, we briefly describe the robust multi-prior Bayesian framework and define our time-varying gasoline price path-through measure.

2.1. Structural VAR with zero and sign restrictions and narrative sign 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).

$$\boldsymbol{A}_0 \boldsymbol{y}_t = \boldsymbol{A}_i \boldsymbol{y}_{t-i} + \boldsymbol{\varepsilon}_t \tag{1}$$

where A_0 is an invertible $n \times n$ matrix; A_i are autoregressive parameters in an $n \times n$ matrix. Structural shocks in an $n \times 1$ vector form denoted as ε_t is Gaussian with mean zero and covariance matrix I_n, the $n \times n$ identity matrix.

The model can be expressed in reduced form as

$$\boldsymbol{y}_t = \boldsymbol{B}_{\mathrm{i}} \boldsymbol{y}_{t-i} + \boldsymbol{u}_t \tag{2}$$

where $B_i = A_t A_0^{-1}$ and $u_t' = \varepsilon_t' A_0^{-1}$ and $E[u_t u_t'] = E[A_0^{-1\prime} \varepsilon_t \varepsilon_t' A_0^{-1}] = E[A_0^{-1\prime} A_0^{-1}] = \Sigma$.

Transfer the model into orthogonal reduced form (Arias et al, 2018) like following:

$$\boldsymbol{y}_t = \boldsymbol{B}_{\mathrm{i}} \boldsymbol{y}_{t-i} + \boldsymbol{\Sigma}_{tr} \mathbf{Q} \boldsymbol{\varepsilon}_t \tag{3}$$

where $\boldsymbol{\Sigma}_{tr}$ is a lower-triangular Cholesky factor of $\boldsymbol{\Sigma}$ with non-negative diagonal elements, and $\mathbf{Q}$ is an $n \times n$ orthonormal matrix. By denoting $\mathbf{A} = [A_1 \cdots A_p]$ and $\mathbf{B} = [B_1 \cdots B_p]$, the matrices $(\mathbf{B}, \Sigma)$ are the reduced-form parameters and $(A_0, \mathbf{A})$ are the structural parameters. Given structural parameters, the structural shocks at time t are $\boldsymbol{\varepsilon}_t'(A_0, \mathbf{A})$.

Following Antolín-Díaz and Rubio-Ramírez (2018), we define impulse response functions and historical decompositions as functions of structural parameters and structural shocks. Narrative sign restrictions use historical decomposition, whereas traditional sign restrictions use impulse response functions. Impulse response functions in matrix form are defined recursively by

$$\mathbf{L}_k(A_0,\mathbf{A}) = \sum_{i=1}^{k} (A_i A_0^{-1})'\mathbf{L}_{k-i}(A_0,\mathbf{A}) \quad \text{for } 1 \le k \le p \tag{4}$$

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

The historical decomposition, i.e., the contribution of the *j*th shock to the observed unexpected change in the *h*th variable between period *t* and $t+\tau$ is

$$\mathbf{H}_{h,j,t,t+\tau}(A_0,\mathbf{A},\boldsymbol{\varepsilon}_t,\cdots\boldsymbol{\varepsilon}_{t+\tau}) = \sum_{k=0}^{\tau} e'_{h,n}\mathbf{L}_k(A_0,\mathbf{A})\, e_{j,n} e'_{j,n}\boldsymbol{\varepsilon}_{t+\tau-k} \tag{5}$$

where $e_{j,n}$ is the *j*the conlumn of I_n, for $1 \le h,j \le n$ and for $\tau \ge 0$.

Traditional sign restrictions can be characterized by the following function, Arias, Rubio-Ramírez, and Waggoner (2018).

$$\Gamma(A_0,\mathbf{A}) = (e'_{1,n}\mathbf{F}(A_0,\mathbf{A})'\mathbf{S}'_1,\ldots,e'_{n,n}\mathbf{F}(A_0,\mathbf{A})'\mathbf{S}'_n)' > 0 \tag{6}$$

Narrative sign restrictions are characterized by three classes. The first class imposes the sign on the *j*th shock at the date, $\tilde{t}$. For example, for a positive shock restriction,

$$e'_{j,n}\boldsymbol{\varepsilon}_{\tilde{t}} > 0 \tag{7}$$

The second class imposes that a contribution of *j*th shock in the *h*th variable at the date, $\tilde{t}$, is larger in absolute terms than contributions of any other shocks. This shock is called the most important driver or Type A restriction on the historical decomposition in Antolín-Díaz and Rubio-Ramírez (2018).

$$\left|\mathbf{H}_{h,j,t,t+\tilde{t}}(A_0,\mathbf{A},\boldsymbol{\varepsilon}_t,\cdots,\boldsymbol{\varepsilon}_{t+\tilde{t}})\right| > \max_{j'\neq j}\left\{\left|\mathbf{H}_{h,j',t,t+\tilde{t}}(A_0,\mathbf{A},\boldsymbol{\varepsilon}_t,\cdots,\boldsymbol{\varepsilon}_{t+\tilde{t}})\right|\right\} \tag{8}$$

The third class imposes that a contribution of *j*th shock in the *h*th variable at the date, $\tilde{t}$, is larger in absolute terms than the sum of contributions of all other shocks. This shock is called the overwhelming driver or Type B restriction on the historical decomposition in Antolín-Díaz and Rubio-Ramírez (2018).

$$\left|\mathbf{H}_{h,j,t,t+\tilde{t}}(A_0, \mathbf{A}, \boldsymbol{\varepsilon}_t, \cdots, \boldsymbol{\varepsilon}_{t+\tilde{t}})\right| > \sum_{j' \neq j} \left\{\left|\mathbf{H}_{h,j',t,t+\tilde{t}}(A_0, \mathbf{A}, \boldsymbol{\varepsilon}_t, \cdots, \boldsymbol{\varepsilon}_{t+\tilde{t}})\right|\right\} \tag{9}$$

The structural parameters of the SVAR model are set-identified by drawing a set of reduced parameters from the posterior distribution, drawing an orthonormal matrix, recovering structural parameters, and checking whether structural parameters satisfy the identification restrictions of zero, traditional signs, and narrative signs.

2.2. Robust Bayesian framework

As argued in the previous section, traditional SVAR uses the median to represent impulse responses. It will cause the problem like following: (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; (3) it has been shown in various empirical studies that the 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. It 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, ...) 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, it is possible that a specific impulse response, when taken out, may extend beyond the confidence interval at some time point after the shock. In order to solve the above two problems, it has been proposed to show the impulse response with the mode (Inoue and Kilian, 2013) and to plot the extraction that satisfies all the constraints (Baumeister and Hamilton, 2020).

In addition, Issues related to the prior distribution have also been identified. When conducting ensemble estimations like SVAR, simply specifying the prior distribution of the structural parameters is insufficient. The posterior distribution of structural parameters and impulse response functions cannot be uniquely determined without specifying the conditional distribution. As a solution, Giacomini et al., 2021 proposed considering all prior distributions that have support over the entire set of orthogonal rotation matrices satisfying zero constraints and sign constraints (and sign normalization conditions) for given structural parameters. As an application, it is suggested that the unique median of impulse response functions used in traditional studies be represented as a median set (the range between the average of the upper bound of the median and the average of the lower bound of the median).

We insert this methodology of robust multi-prior Bayesian framework (Giacomini et al., 2021) into the Forbes model to calculate the gasoline price path-through. In terms of results, the robust Bayesian approach provides a broader set of credible regions, so any research results are less likely to reject the null hypothesis. So, the effects will more likely be found as not statistically significant. On the other hand, if any effects are statistically significant with their 'robust Bayesian' approach, the results can be expected to be more credible.

As suggested by Baumeister and Hamilton (2015, 2020), it is to show all series of impulse response functions, resulting in a 'shotgun' figure. In this paper, we follow the methodology of Giacomini and Kitagawa (2021), which proposes to compute the set of posterior means and the associated robust credible regions. Specifically, Giacomini and Kitagawa (2021) add another step after obtaining a draw, from the posterior distribution of reduced form parameters,ϕ, that satisfies zero and traditional sign restrictions. The minimum and maximum values of impulse responses are computed after obtaining $\tilde{K}$ draws.[3] Then, this step is repeated M times to obtain the set of posterior means, $l(\phi_m)$ and $u(\phi_m)$, and the smallest credible region.

We will describe 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, $\widehat{\phi} = (\widehat{\mathbf{B}}, \widehat{\Sigma})$. 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.[4] Note that zero restrictions are imposed at this stage for the construction of $\tilde{Q}$.

Then, as the second step, impulse response functions, $\mathbf{L}_k(\tilde{A}_0, \tilde{\mathbf{A}})$ as in Equation (4), are calculated and checked for whether traditional sign restrictions, 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.

In the conventional structural VAR method, by repeating these two steps, the

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

[4] In Giacomini and Kitagawa (2021), they use the linear projection method (Step 2.1. in Algorithm 1) and provides the QR decomposition method as an alternative.

researchers obtain the M sets of impulse response functions. However, the multi-prior approach in the robust Bayesian structural VAR method of Giacomini and Kitagawa (2021) requires obtaining the $\tilde{K}$ set of impulse response functions by altering $\tilde{Q}$ for a fixed $Chol(\tilde{\Sigma})$. By using the superscript h for denoting a different draw that satisfies all restrictions for this $\tilde{K}$ set, the pointwise minimum and pointwise maximum are defined as $l(\tilde{\phi})$ and $u(\tilde{\phi})$ as follows:

$$l(\tilde{\phi}) = \min_h L_k^h(\tilde{A}_0^h, \tilde{\mathbf{A}}^h) \tag{10}$$

$$u(\tilde{\phi}) = \max_h L_k^h(\tilde{A}_0^h, \tilde{\mathbf{A}}^h) \tag{11}$$

With this additional step, $l(\tilde{\phi})$ and $u(\tilde{\phi})$ in Equations (10) and (11) are obtained M times by alternative $\tilde{\phi} = (\tilde{\mathbf{B}}, \tilde{\Sigma})$.

The set of posterior means is obtained as the interval by taking the sample average of Equations (10) as the lower bound and (11) as the upper bound. The robust credible region with credibility $\alpha \in (0, 1)$ is a set on which the posterior credibility of the parameters of interest is at least α, no matter which posterior is chosen within the class, Giacomini and Kitagawa (2021).

2.3. Gasoline price pass-through definition

One of the purposes of this paper focuses on understanding the time-varying changes in gasoline price pass-through into the consumer price index, which depends on the underlying shocks. After obtaining impulse responses of gasoline price and consumer price index from individual structural shocks, we can define shock-specific gasoline price pass-through as the ratio of the cumulated changes in consumer price index to the cumulated changes in 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 domestic prices (or import prices) to each shock and the impulse response of nominal exchange rates to each shock. If the impulse response of variable j after τ periods due to shock (i) is defined as IRj(i,τ), then the gasoline price pass-through into consumer price is defined as follows[5].

$$GPPT(i, \tau) \equiv \frac{\sum_{t=0}^{\tau} IR_p(i, t)}{\sum_{t=0}^{\tau} IR_s(i, t)} \tag{12}$$

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[5] The gasoline price path-through is defined between -1 and 1.

Therefore, gasoline price pass-throughs measured in this approach are time-varying and will also change based on the corresponding shock. That will allow us to identify whether gasoline price pass-through changes in response to corresponding shocks and explore the economic implications of this pass-through change. This path-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 Identification Strategy

3.1. Data

Our model contains six variables. The economic activity is proxied by seasonally adjusted World (OECD) Industrial production growth by the OECD Statistics. The growth rate of global oil production (supply shock), and the real price of crude oil (demand shock) by the Energy Information Administration. The consumption-tax-adjusted consumer price index and gasoline price are 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. Except for World (OECD) Industrial production and the growth rate of global oil production, all data are natural logarithms series and proceed by the Hodrick-Prescott filter.

3.2. SVAR model

Our SVAR model is defined based on equation (3) applied to the Japanese economy[6], which can be expressed as follows.

$$\begin{aligned} &\left[\ln CPI_t \;\; \ln Gasoline_t \;\; \Delta\, Oil\ production_t \;\; \Delta\, economic\ activity_t \;\; \ln Oil\ demand_t \;\; \ln neer_t \right] A_0 = \\ &\sum_{i=1}^{6} \left[\ln CPI_{t-i} \;\; \ln Gasoline_{t-i} \;\; \Delta\, Oil\ production_{t-i} \;\; \ln economic\ activity_{t-i} \;\; \ln Oil\ demand_{t-i} \;\; \ln neer_{t-i} \right] A_i + \varepsilon_t \end{aligned} \tag{13}$$

where CPI is the consumer price index, Gasoline is the domestic gasoline price, Δ oil production is the growth rate of global oil production, Δ economic activity is the World (OECD) Industrial production growth, Δ oil demand is the real price of crude oil, and neer is a nominal effective exchange rate. To identify the structural shocks, we put the number of zero, sign, and narrative sign restrictions on the impulse responses of

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[6] Based on the Akaike information criterion, we chose the number of lags to be six. Therefore, the beginning of the sample starts from the seventh quarter of 1995 in the regression.

endogenous variables to the corresponding structural shocks.

3.3. Zero and sign restrictions

Table 1 presents the short-run zero, long-run zero, and sign restrictions. These restrictions are consistent with some previous studies. The top panel represents short-run zero and traditional sign restrictions. First, following Kilian et al., (2009), we use three short-run zero restrictions to show the relationship between three type oil shocks. These assumes that oil producers can be free to respond to both lagged values of oil prices and global economic activity, but considering the adjusting costs and the uncertainty, oil production will not respond to economic activity and oil demand shocks in the same month. At the same time, the oil demand shock will not influence global economic activity in the same month.

Second, the following sign restrictions have been devised. A positive nominal gasoline price shock is assumed to raise the real price of gasoline and which in turn affects the consumer price index in the same period (Kilian and Zhou, 2022a). An exchange rate shock, which is shown as the Japanese yen appreciation, has a negative impact 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 international crude oil market (Kilian and Zhou, 2022b). Furthermore, Japan's gasoline prices are on the receiving end of the oil shock and will not have opposite influence.

3.4. Narrative sign restrictions

We have selected two crucial episodes in which the effect of 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. World trade experienced a sudden and sharp fall. The narrative restriction for this episode is the following: the negative economic activity shock deteriorated the industrial production of the World, and its contribution was overwhelming. (ii) The second episode is the 2020 Russia–Saudi Arabia oil price war. On 9 April, OPEC and Russia agreed to reduce the crude oil production from the following month. This oil production reduce is also the most significant one during our entire sample period. We impose a narrative restriction that the oil supply shock decreases the oil production, and its contribution is overwhelming.

4. Empirical Results

4.1. Robust Bayesian SVAR Estimates

Figure 4 represents the cumulated impulse responses on CPI with respect to each structural shock. From Figure 4, we can observe that can be rejected for all five structural (gasoline price, exchange rate, oil supply, economic activity, and oil demand) shocks. These results indicate that Japanese consumer prices are not directly affected by these shocks. Figure 5 represents the cumulated impulse responses on gasoline price with respect to each structural shock. We can classify these four shocks in two groups. The first group of shocks do not affect Japan's gasoline price, null hypothesis cannot be rejected for exchange rate, oil supply and economic activity shocks. For the second group, except for extremely few draws, all 1000 draws' impulse responses are persistently positive. An increase in the gasoline price is associated with a positive oil demand shock, and the median impulse response is approximately 0.05.

Figure 6 represents the impulse responses of the cumulated gasoline pass-throughs with respect to the five structural shocks. Zero gasoline price pass-through cannot be rejected for gasoline price, exchange rate, oil supply, economic activity, and oil demand shocks. All the five shocks do not affect Japan's inflation by their effect on gasoline price movements.

4.2. Robustness check

First, in the main analysis, we chose two episodes of 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 robust Bayesian estimation results without narrative sign restrictions while maintaining everything else intact.

Second, the COVID-19 pandemic in 2020 and 2021 lowered economic activities 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 oil supply shock. However, there may also exist huge influence from the economic activity shock or some other exogenous shocks during this period. Considering the complexity of the pandemic period, we also estimated the same SVAR model with the sample period ending in January 2020, just before the pandemic breakout in Japan.

However, based on the results from Figure A1 to A6, both the two robustness check results are almost consistent with the main analysis. The exogenous shocks did not affect Japan's inflation in the post-pandemic period. However, they may have contributed to affecting it before the pandemic period. Meanwhile, the pervasive effect of oil demand shock to gasoline price remains statistically significant regardless of whether the pandemic period is included in the sample.

4.3. Discussions

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

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

Renou-Maissant (2019) investigate 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 point out 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 Japan's effect is the lowest among the eight countries. From the time varying paths of the oil pass-through coefficient we can know, this parameter in Japan is started to decline since around 2009. Considering the difference in the sample period, this may be one of the reasons why our CPI's response to oil shocks is different from Yoshizaki and Haomori (2014)

In addition to the above, Antonio and Luis (2022) analyzed oil price fluctuations and headline inflation, focusing on the Euro-area, the UK, and Japan. As a result, they found that, unlike in other countries where oil prices are 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 past 18 months until the end of our sample period, Japan's inflation growth sustained around 3% due to the influence of external shocks such as the COVID-19 pandemic and Russia's invasion of Ukraine. Still, it remains uncertain whether this means 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 shock on Japan's CPI and gasoline prices, and then we estimate the gasoline price pass-through into CPI in Japan. As the result, we only find a positive influence of oil demand shock to gasoline price. For Japan's CPI, the zero gasoline price pass-through cannot be rejected for gasoline price, exchange rate, oil supply, economic activity, and oil demand shocks. As some previous studies have pointed out, we have also confirmed the particularity of the relationship between Japan's CPI and crude oil shocks. As for the reason, can be partially interpreted by the lower oil intensity of Japan and the higher proportion of taxes in oil prices. The higher the fuel tax wedge, the smaller the proportional impact on prices of a given rise in oil prices.

As proposed by Cologni and Manera (2008), for some countries (like US) a significant part of the effects of the oil price shock is due to the monetary policy reaction. As 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 quantitative easing monetary policy, it is difficult to implement effective policy adjustments to deal with exogenous crude oil shocks. If a sustained negative crude oil demand shock occurs, it is likely to have an impact on Japan's gasoline prices, and thus on CPI. The BOJ must continue to monitor oil prices fluctuations closely, especially when they are prolonged over time.

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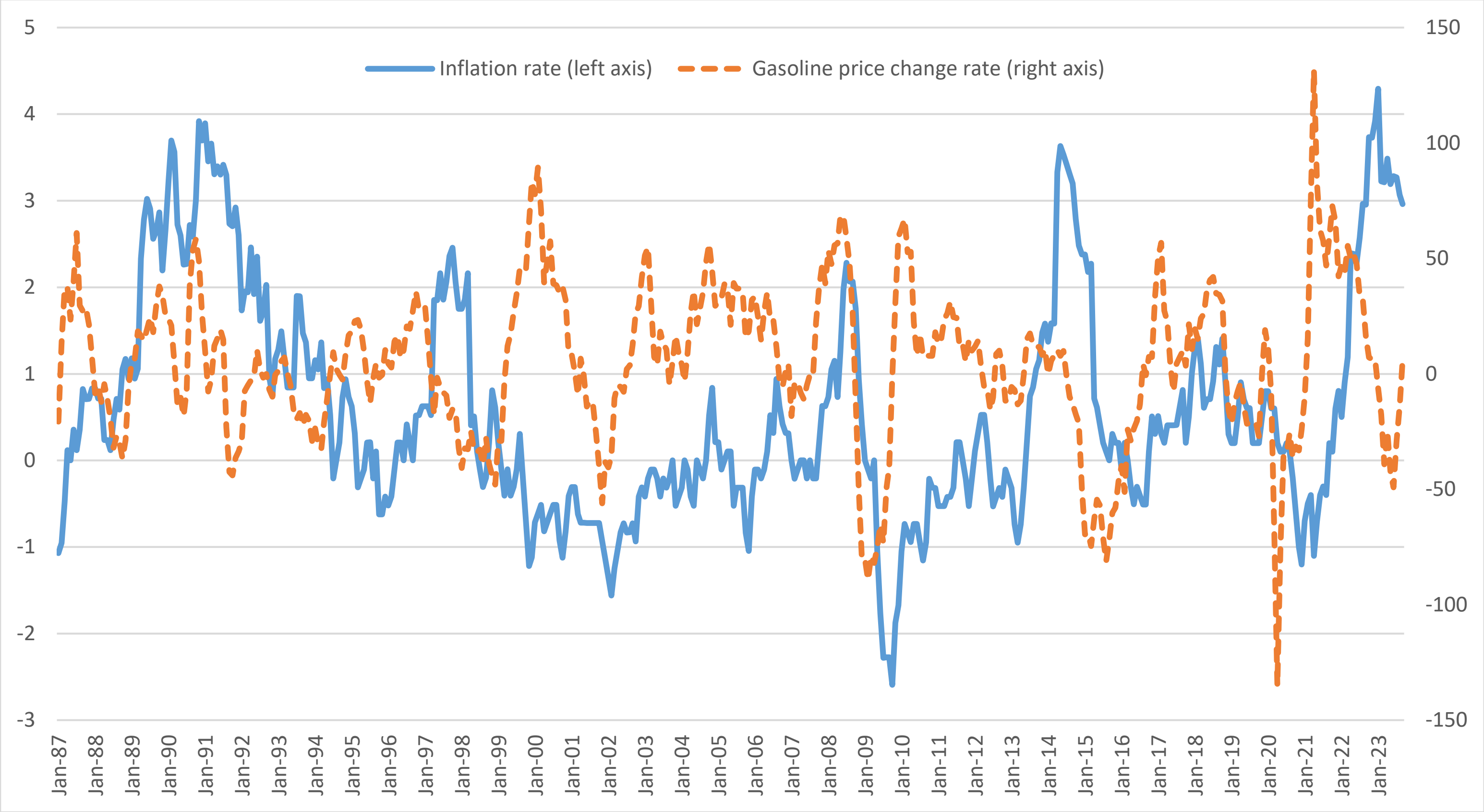
Table 1. Identification restrictions

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

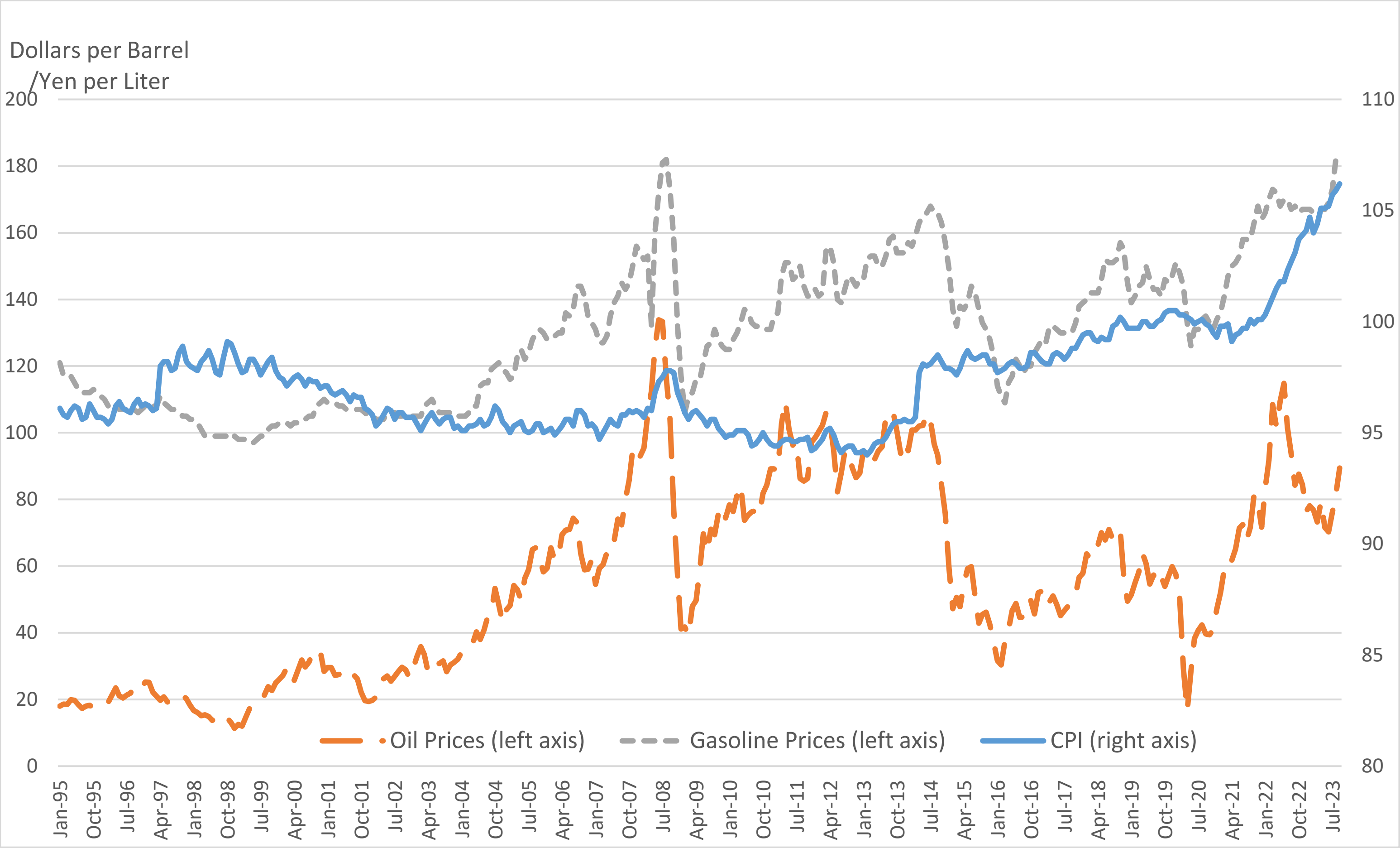
Note: A '0', '+', or '-' sign indicates that the impulse response of the variable listed in the row to the shock in the column is zero, positive, or negative, respectively, in the quarter the shock occurs and in the following quarter.

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



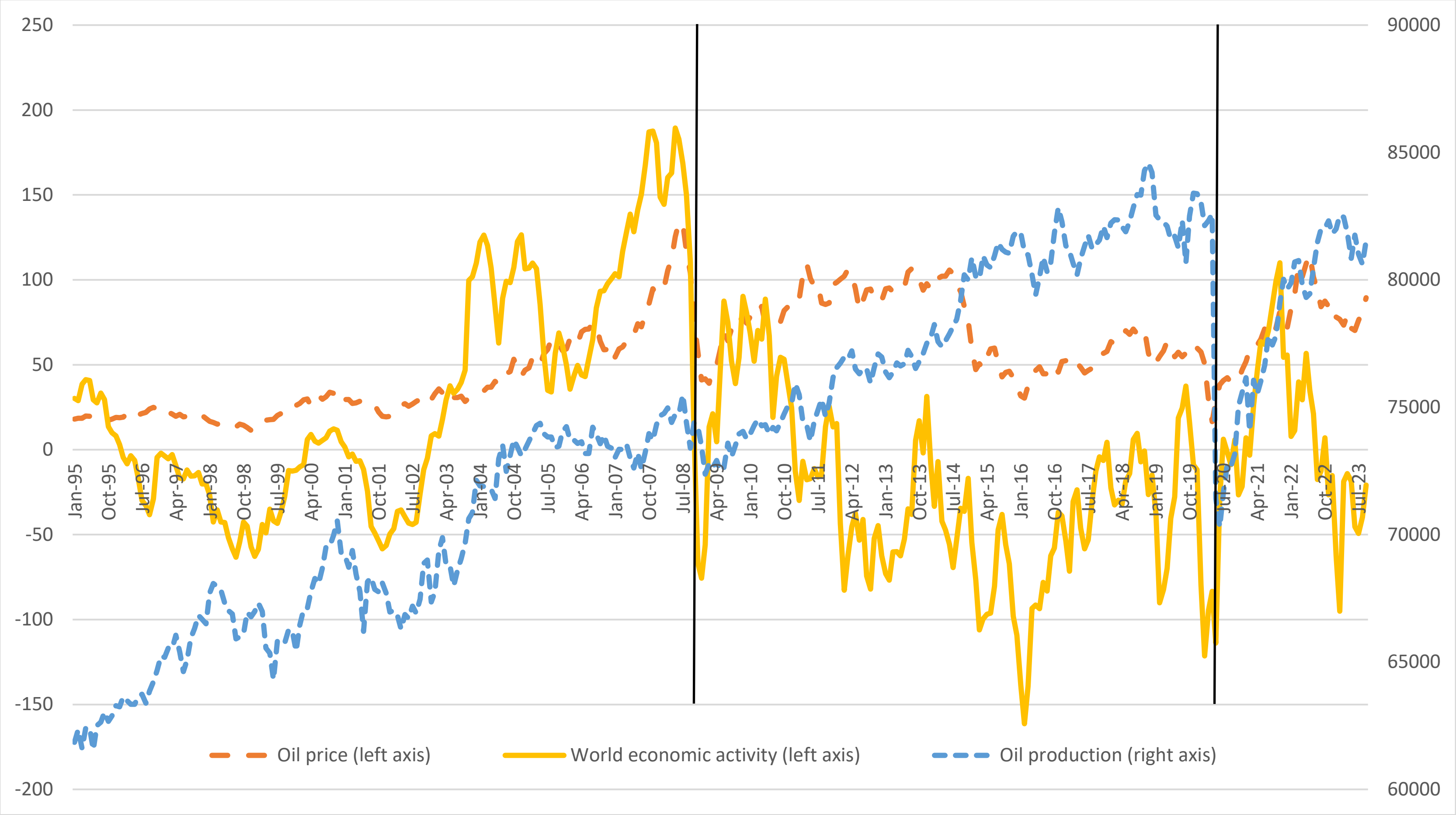
Notes: The inflation rate is the log difference of the consumer price index adjusted for consumption tax, and the gasoline price change rate is the log difference of the gasoline prices in the Japanese market, measured for the current month's change from the same month in the previous year.

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



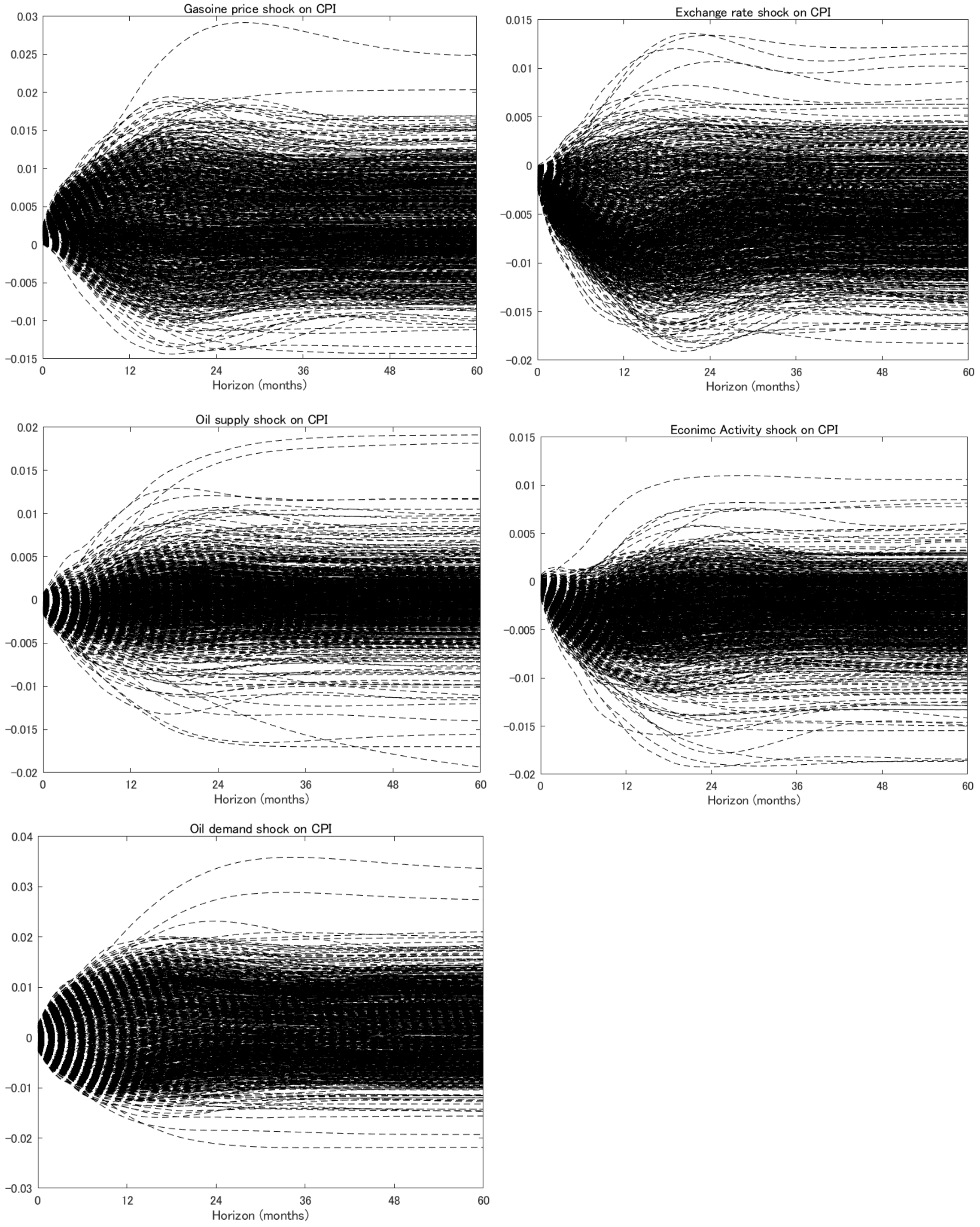
Notes: The oil price is the spot price of crude oil (Dollars per Barrel). Gasoline prices are the value of retail prices. The CPI is the consumer price index adjusted for consumption tax.

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



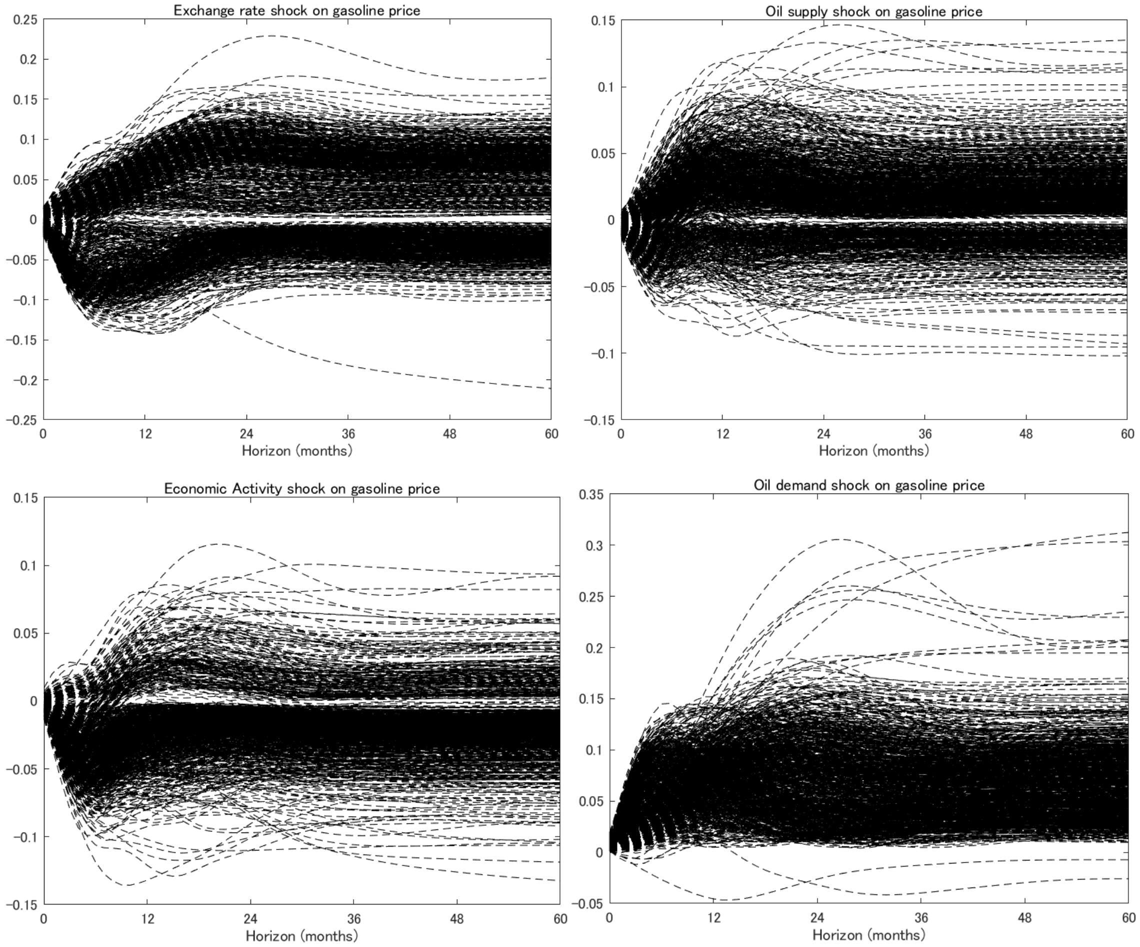
Notes: The oil price is the spot price of crude oil (Dollars per Barrel). The global real economic activity is the Index of Global Real Economic Activity. The oil production is the worldwide crude oil production (Mb/d)

Figure 4. Cumulated impulse response function on CPI



Notes: The black dashed line represents the 1000 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2023M9.

Figure 5. Cumulated impulse response functions on gasoline price



Exchange rate shock on gasoline price

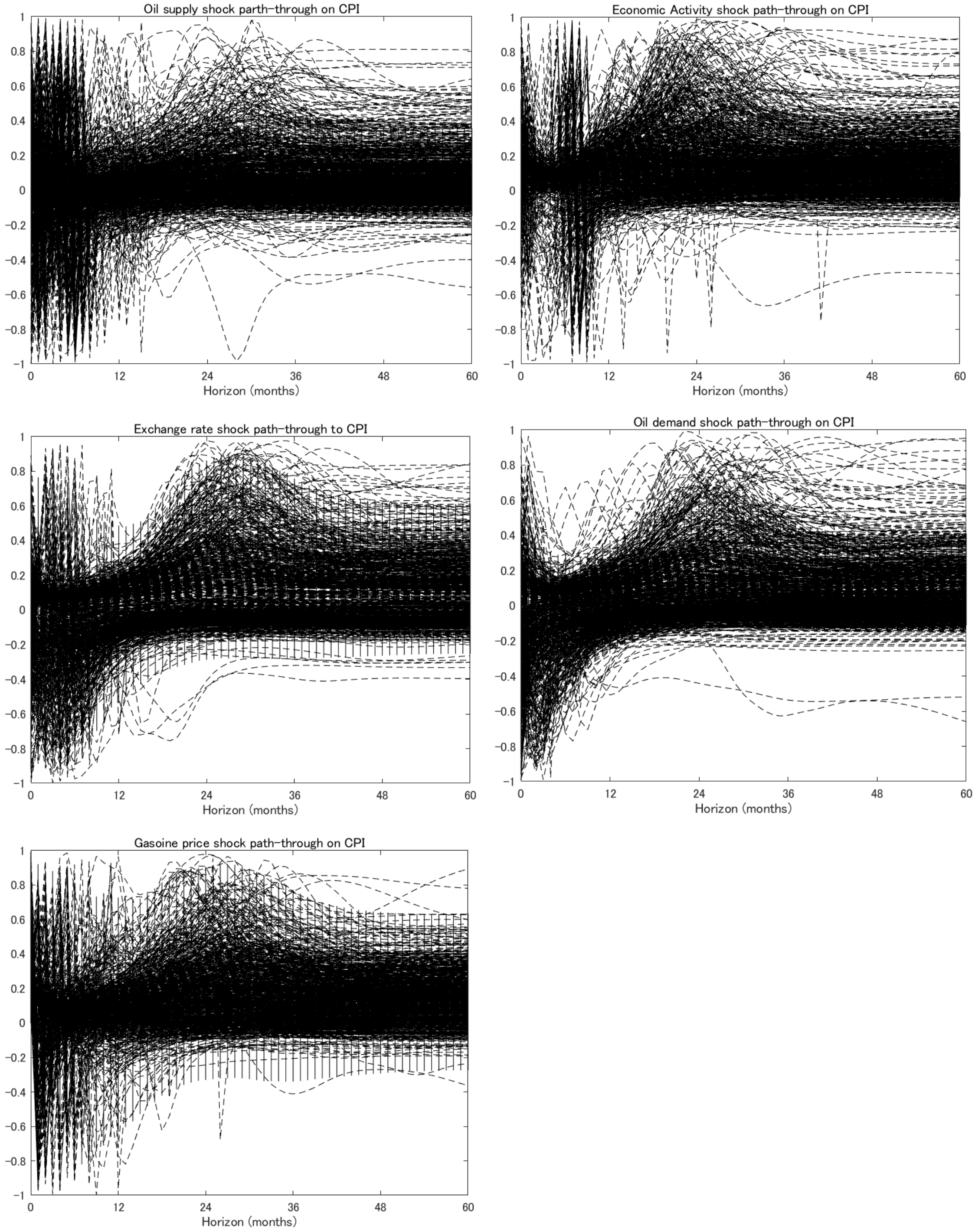
Oil supply shock on gasoline price

Economic Activity shock on gasoline price

Oil demand shock on gasoline price

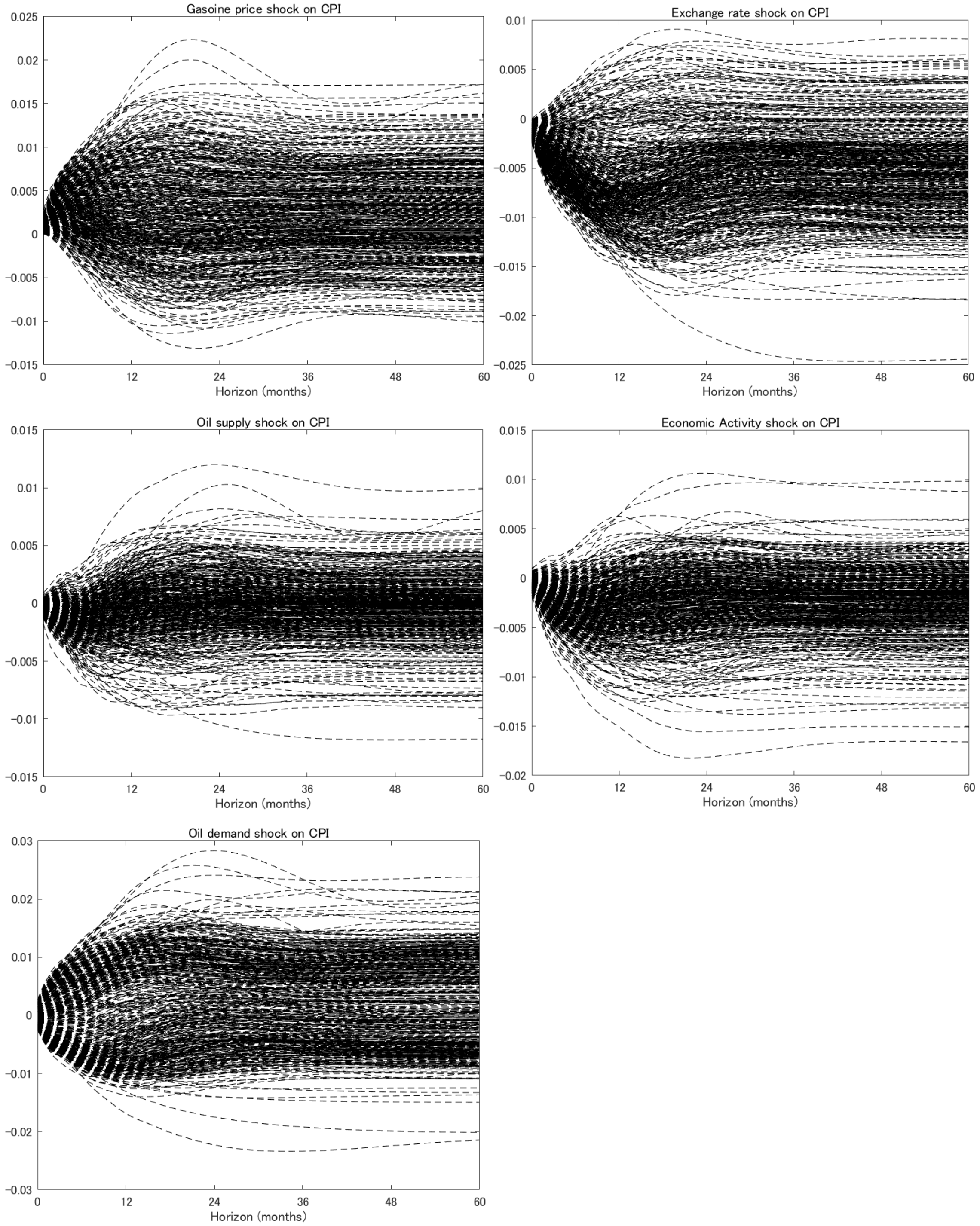
Notes: The black dashed line represents the 1000 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2023M9.

Figure 6. Gasoline price path-through on CPI



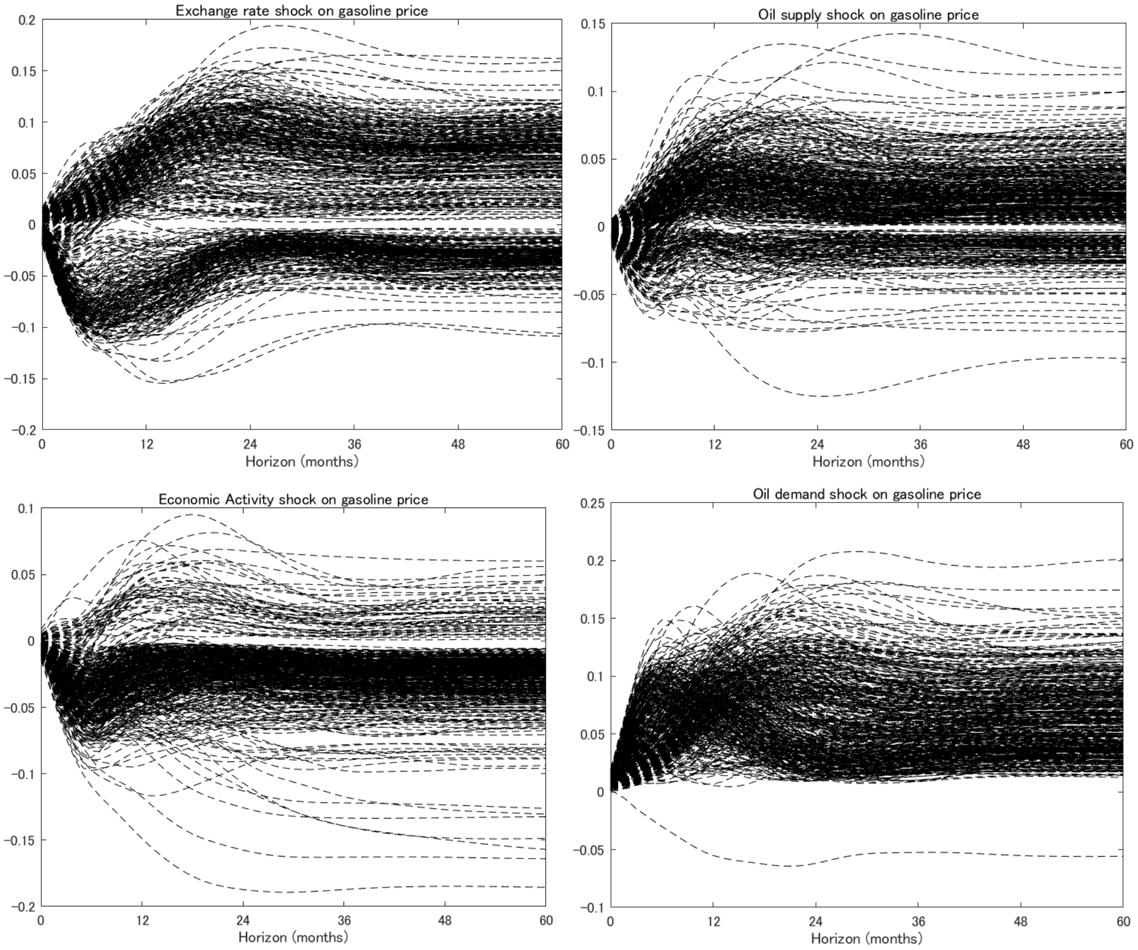
Notes: The black dashed line represents the 1000 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2023M9.

(Appendix) Figure A1. Cumulated impulse response function on CPI, non-narrative sign restrictions



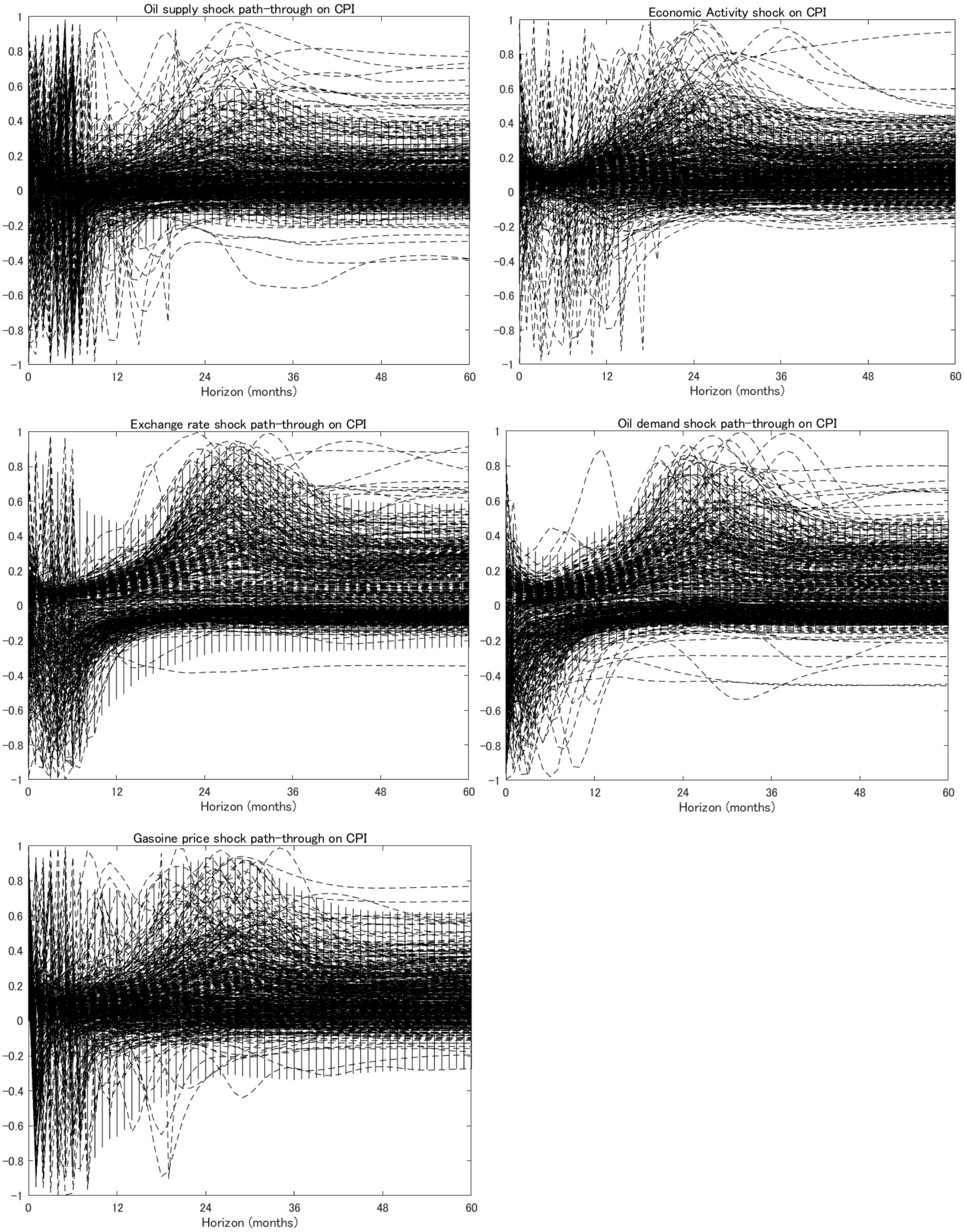
Notes: The black dashed line represents the 500 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2023M9.

(Appendix) Figure A2. Cumulated impulse response functions on gasoline price, non-narrative sign restrictions



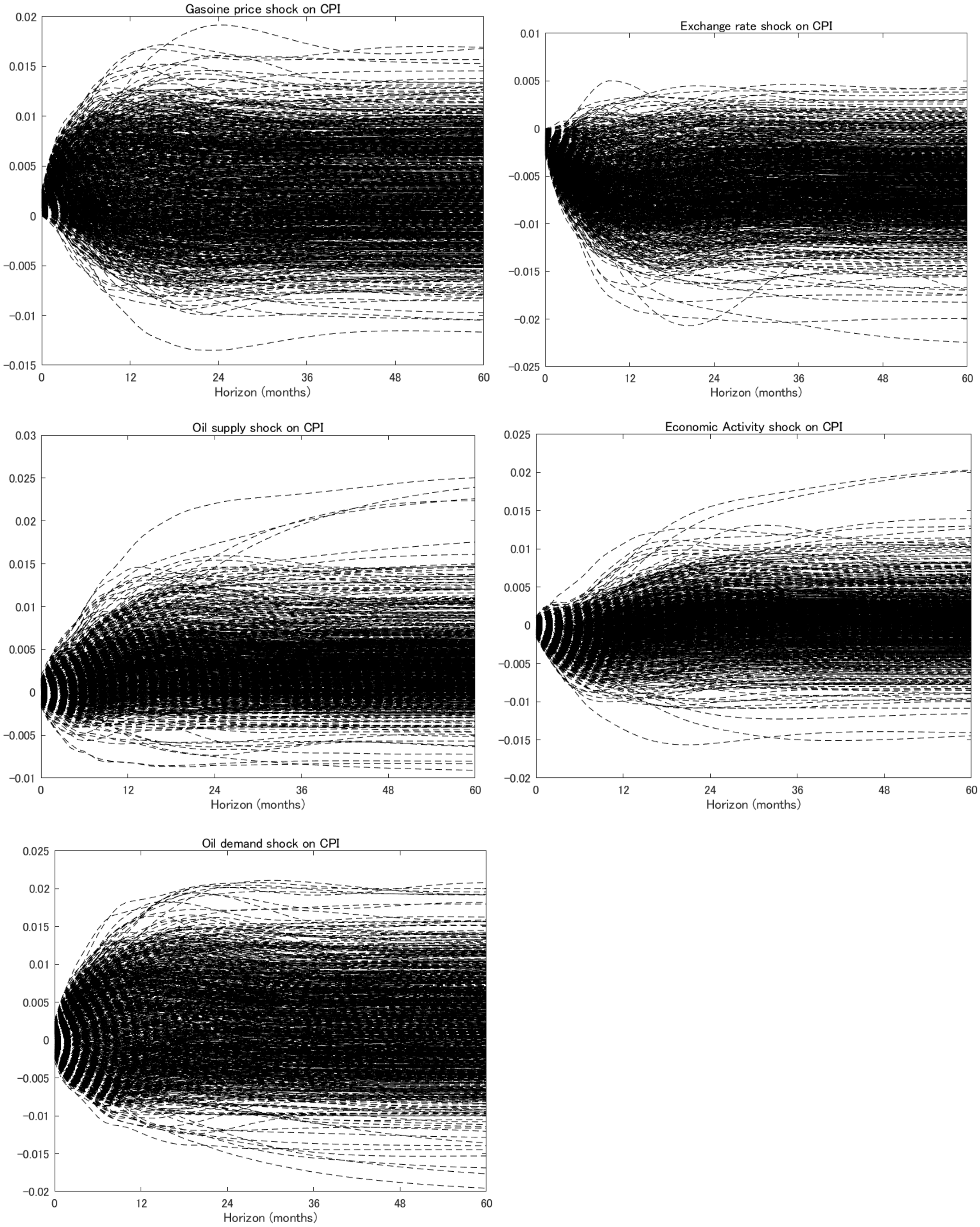
Notes: The black dashed line represents the 500 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2023M9.

(Appendix) Figure A3. Gasoline price path-through on CPI, non-narrative sign restrictions



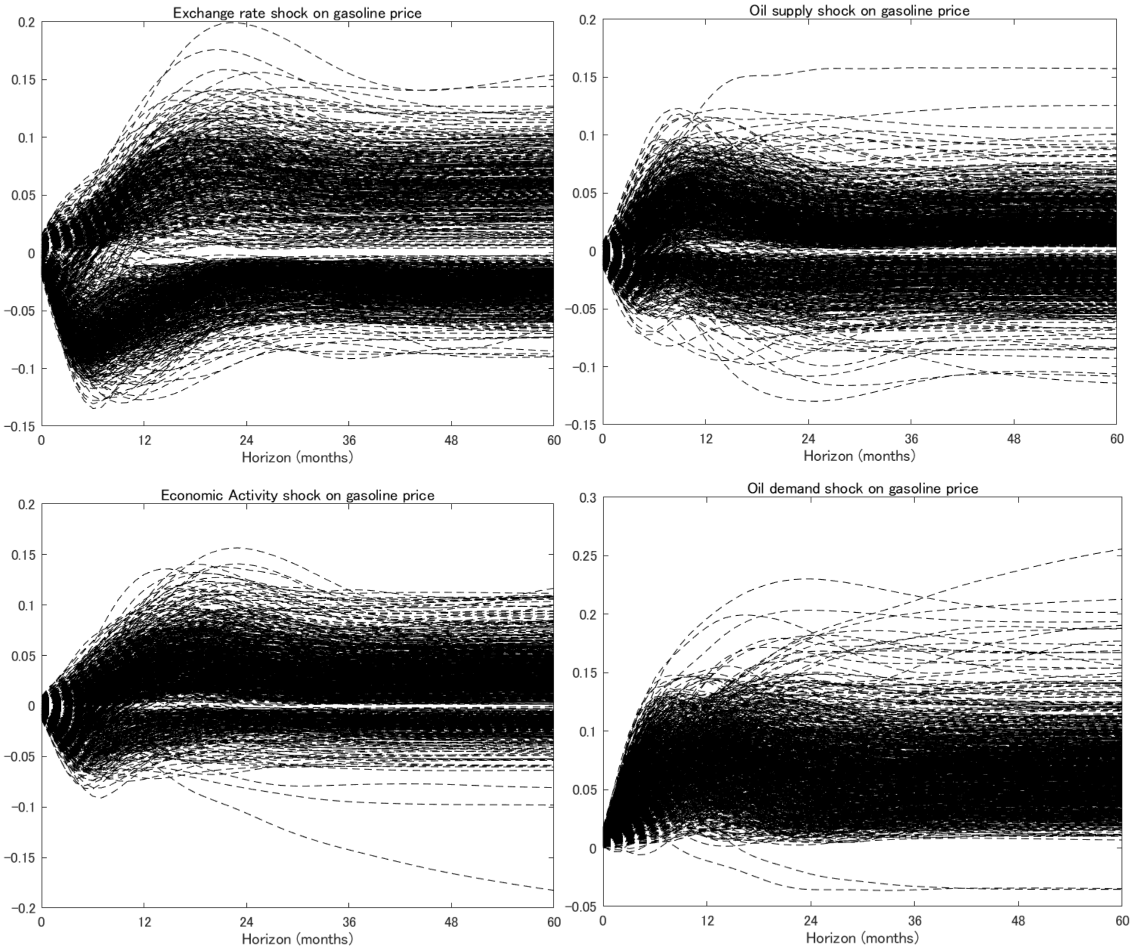
Notes: The black dashed line represents the 500 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2023M9.

(Appendix) Figure A4. Cumulated impulse response function on CPI, short period



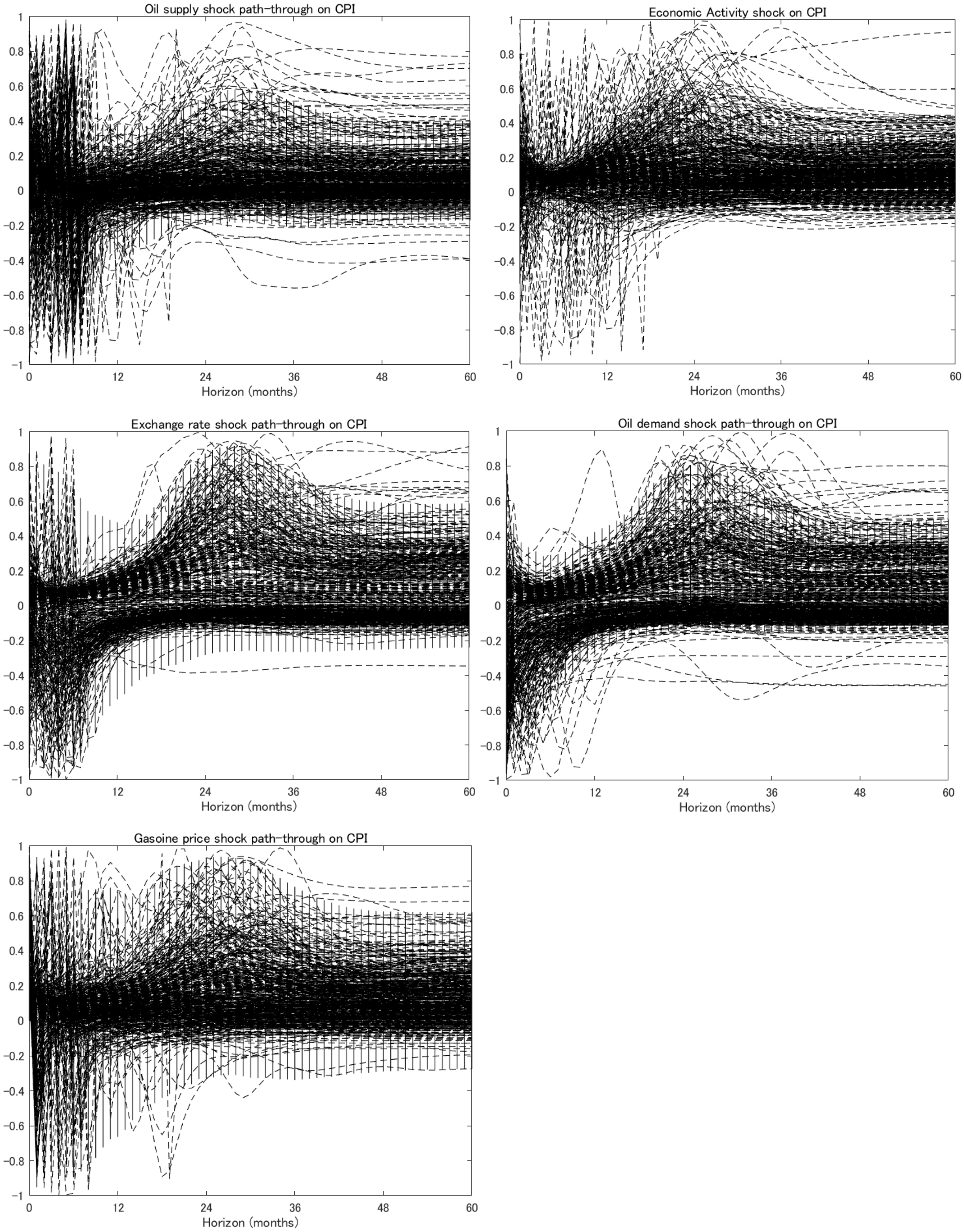
Notes: The black dashed line represents the 1000 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2020M1.

(Appendix) Figure A5. Cumulated impulse response functions on gasoline price, short period



Notes: The black dashed line represents the 1000 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2020M1.

(Appendix) Figure A6. Gasoline price path-through on CPI, short period



Notes: The black dashed line represents the 1000 draws that satisfied the identification restriction. The horizontal axis is the number of quarters after the shock. The data sample is from 1995M1 to 2020M1.