Oil shocks and regional heterogeneity: Analysis using Japanese prefecture-level data

Tuan Khai Vu*
Housei University

Hayato Nakata**
Meisei University

May, 2019
(Preliminary)

Abstract

This paper studies the effects of world market oil price fluctuations on the regional economies of Japan and analyzes how these effects are related to various types of heterogeneity across these regions. We use a VAR with block exogeneity to identify oil shocks and their effects on the regional economies. We find that the regional heterogeneity in natural and socio-economic environment does affect the way the regional economies respond to oil shocks. A region with colder winter, higher number of cars owned per person, more fuel consumption, or lower value added per person in industry and agriculture has the price level affected more by oil market specific shocks. A region that specializes more in the automobile industry has output driven more by oil demand shocks coming from global economic activity.

Keywords: oil price fluctuations, Japanese regional economies, VAR with block exogeneity.
JEL codes: F41, Q43, R11.

1. Introduction

This paper studies the effects of world market oil price fluctuations on the regional economies of Japan and analyzes how these effects are related to various types of heterogeneity across these regions.

Since 2000, the sharp rise in the world-market oil price has triggered a large number of empirical studies aiming to analyze effects of oil price shocks on the macroeconomy. Recently some studies look at the differences in the effects of oil price shocks across countries (see, e.g., Peersman and Robays 2009 and Vu and Nakata 2018a), or across regions within the same country (see our previous study Vu and Nakata 2016).

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* Faculty of Economics, Hosei University. Mailing address: 4342 Aihara-machi, Machida-shi, Tokyo 194-0298, Japan. E-mail: vu.tuankhai@hosei-u.ac.jp.
** Faculty of Economics, Meisei University. Mailing address: 2-1-1 Hodokubo, Hino-shi, Tokyo 191-8506, Japan. E-mail: hnakata@econ.meisei-u.ac.jp.

However, very few papers investigate the causes of this heterogeneity. Peersman and Robay (2009) examine the relationship between the impacts of oil price on wages, or GDP deflator and strictness of employment legislation in Euro area countries. Vu and Nakata (2018a) find a negative relationship between the contributions of oil price shocks to the variances of CPI and IIP and the oil production/consumption ratio in ASEAN countries. Using regional data of Japan, Vu and Nakata (2016) analyze the relationship between the effects of oil price on CPI, IIP and the climate condition and industrial structure in these regions. A shortcoming of these studies is that they cannot carry out formal statistical tests due to the lack of enough observations in the sample used, and as a result, they have to rely on investigation using correlation coefficient or scatter diagram.

The present paper aims to overcome this problem by using a Japanese prefecture-level data set. Our data set consists of data on 47 prefectures of Japan and spans a period of over more than 30 years. We analyze the effects of oil price fluctuations on regional economies in Japan, and examine the factors affecting the regional heterogeneity.

It is worth noting that Japan is suitable for an analysis of the regional differences in the effects of oil price shocks because regions in Japan are quite diverse in several dimensions. For example, the Japanese archipelago stretches over 3000 kilometers from northeast to southwest, possessing a large difference in climate and geographical conditions between regions. In addition, there is also considerable regional heterogeneity in economic structure. Therefore, using prefecture-level data of Japan with such characteristics, our approach can identify the regional heterogeneity in the effects of oil price shocks.

We employ the model of structural vector autoregression (VAR) with block exogeneity used in Vu and Nakata (2018a), which consists the world oil market as the exogenous block and the economy of each prefecture of Japan as the endogenous block. The latter block, which is the focus of our study, is taken as a small open economy and includes such variables as the price level (CPI) and output (IIP) of each prefecture. In the former block, following Kilian (2009) we identify the three types of oil shocks, namely, oil supply shock, shock to aggregate demand for oil, and oil-market specific demand shock.

We estimate the VAR model for each prefecture to reveal the effects of oil shocks on the prefectural economy using conventional tools such as impulse response function and variance decomposition. We then analyze the differences in the effects of oil shocks across the prefectures, and investigate how those differences are related to the heterogeneity of the prefectures. The investigation is conducted by regressing the VAR results on the effects of oil shocks on such factors as climate condition, the specialization coefficient in automobile industry, value added per person in agriculture, industry, and services, the number of cars owned per person and so on. The number of prefectures in Japan is large enough to allow us to perform these formal statistic exercises.

The rest of the paper is organized as follows. Section 2 presents our empirical methodology.

Section 3 describes the data used in our empirical study. In Section 4, we present our empirical results. Section 5 provides conclusions.

2. Empirical Methodology

In this section, we describe our empirical framework to identify the effects of oil shocks in each of the regions in Japan and then analyze how these effects are related to the various types of regional heterogeneity.

To identify the effects of oil shocks in each of the regions in Japan we use of a structural VAR with block exogeneity, which we have used in several previous studies (see, e.g., Vu and Nakata 2018a). Our VAR model comprises two blocks, namely the world oil market and the economy of a region in Japan. The structural form of our model is as follows.

$$\begin{bmatrix} C_{11} & 0 \\ C_{21} & C_{22} \end{bmatrix} \begin{bmatrix} y_{1t} \\ y_{2t} \end{bmatrix} = \begin{bmatrix} B_{11}(L) & 0 \\ B_{21}(L) & B_{22}(L) \end{bmatrix} \begin{bmatrix} y_{1t-1} \\ y_{2t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix} \qquad (1)$$

Here, t denotes time, which is a month in this study. $y_1 \equiv [\Delta\log(oilprod), globrea, \ \log(noilp)]'$ is a vector of three variables of the world oil market, where $oilprod, globrea$ and $noilp$ are respectively the world oil production, an index of global real activity, and the world market nominal oil price. The modeling of the world oil market block is drawn on Kilian (2009). y_{2t} is vector of variables of a Japanese regional economy, and in the estimation in this paper we include the first log-difference of the price level and output of the region, i.e., $y_2 \equiv [\Delta\log(cpi), \Delta\log(iip)]'$. C_{ij} are coefficient matrices and $B_{ij}(L)$ are polynomials made up from coefficient matrices in the lag operator. $\varepsilon_1, \varepsilon_2$ are vector of structural shocks in the two blocks, among which ε_1 consists of three types of shocks, namely, oil supply shock (*oilsup* shock), oil demand shock from global economic activity (*aggdem* shock), and oil market specific demand shock (*oilspedem* shock).

The block exogeneity structure is captured by the assumption $C_{12} = 0$ and $B_{12}(L) = 0$ in (1), that is, we treat a region in Japan as a small open economy whose variables and structural shocks do not affect variables in the world oil market block. This assumption is justified by the fact that the economic size of a prefecture in Japan is very small compared to the world oil market.

The structural form in (1) can be rewritten separately for each block as follows.

$$C_{11}y_{1t} = B_{11}(L)y_{1t-1} + \varepsilon_{1t} \qquad (2)$$

$$C_{21}y_{1t} + C_{22}y_{2t} = B_{21}(L)y_{1t-1} + B_{22}(L)y_{2t-1} + \varepsilon_{2t} \qquad (3)$$

The block of the world oil market in equation (2) can be transformed to the reduced form:

$$y_{1t} = C_{11}^{-1}B_{11}(L)y_{1t-1} + C_{11}^{-1}\varepsilon_{1t} \qquad (4)$$

The reduced-form VAR in (4) can be estimated using OLS. In order to identify C_{11}^{-1}, and thus the structural shocks ε_{1t} in the world oil market block, we follow Kilian (2009) to impose a recursive structure on C_{11}^{-1}. This has the following implications for the relationships between the variables in this block: (i) oil production level is not affected contemporaneously by global economic activity and the oil price; and (ii) global economic activity is not affected contemporaneously by oil market specific shock in the same month.

As for the block of the Japanese regional economy, equation (3) can be transformed to the reduced form:

$$y_{2t} = D_{21}(L)y_{1t-1} + D_{22}(L)y_{2t-1} - C_{22}^{-1}C_{21}C_{11}^{-1}\varepsilon_{1t} + C_{22}^{-1}\varepsilon_{2t} \quad (5)$$

Here, D_{21} , and D_{22} are the polynomial of coefficient matrices $D_{21} \equiv C_{22}^{-1}B_{21}(L) - C_{22}^{-1}C_{21}C_{11}^{-1}B_{11}(L)$, and $D_{21} \equiv C_{22}^{-1}B_{22}(L)$. Because our focus is on the responses of variables in regional economy to structural shocks in world oil market block, we need to identify the coefficient matrix $A_{21} \equiv C_{22}^{-1}C_{21}C_{11}^{-1}$. This can be done by regressing the residual $u_{2t} \equiv -C_{22}^{-1}C_{21}C_{11}^{-1}\varepsilon_{1t} + C_{22}^{-1}\varepsilon_{2t}$ obtained from the estimation of (5) on ε_{1t}. It is worth noting that our approach does not require to specify the structure of regional economy and therefore we can avoid imposing on the VAR further assumptions, many of which are ad hoc and often unrealistic. This is an important advantage of our approach compared with those using the conventional VAR.

Our next step is to analyze how the effects of oil shocks are related to the heterogeneity across the regions. We do this by regressing regional variance decomposition results in the VARX model described above on a number of variables measuring the regional natural and socio-economic environment, such as the average temperature during winter, fuel consumption per person, the degree of specialization in automobile industry, the number of cars owned per person, value added per person in agriculture, industry, and services.

3. Data and Estimation

Two datasets are used in our study. First, in the estimation of the VAR model, we use monthly data of the period January 2000 to March 2015. For the world oil market block, we collect oil production data from the website of the U.S. Energy Information Administration. The index constructed and made available online by Lutz Kilian is used as a measure of global real economic activity. The nominal oil price data is taken from the IMF's Primary Commodity Price Statistics. The original oil production data and oil price data are transformed to logarithms and then multiplied by 100 so that the IRFs correspond to the rates of change in percentage.

For the regional economy block, we use the consumer price index (CPI) and the index of industrial production (IIP) of 47 prefectures of Japan taken from the Nikkei-NEEDS-CDCIs database. Both indicators are seasonally adjusted and transformed to the first differences of their logarithms and multiplied by 100.

The reduced-form of the VARX described in the previous section is estimated with twelve lags (taking into account the monthly data used in estimation) and a constant term.

The second dataset we use here contains various indicators on the natural and socio-economic environment of regions in Japan, as explained as the end of the last section. These data are calculated as the period average, with the periods varying across the indicators but roughly coinciding with the sample period of the first dataset. More details of the regional data of Japan are given in the appendix.

4. Results and Analysis

We first look at a few cases in each of which the IRFs of a pair of prefectures with a difference in some characteristic are compared. The results are shown in Figure 1. In Case 1, two prefectures with a large difference in temperature in winter, Hokkaido (-2.5°C) and Okinawa (17.6°C), are compared. The most outstanding difference in the effects of oil shocks in this case is the IRFs of CPI to the oil market specific demand shock: CPI rises much more in Hokkaido (the northernmost prefecture in Japan) than in Okinawa (the southernmost one), with the gap between the two is nearly 0.1% in the horizon of 24 months. Note that the oil shock here raises the oil price by 1%.

Quite similar results are also observed in Cases 2 and 4. All of these results are intuitive in that a region with a colder winter of with more cars owned per person, or with more fuel consumed will have larger weights of goods and services whose prices are affected by the rise in oil price in the world market, and therefore the price level of this region will rise more.

Case 3 looks at the difference in the degree of specialization in the automobile industry, which is one of the main industries of Japan in terms of both domestic production and exports. Here a comparison is made between two prefectures with a large difference in the coefficient of specialization in the automobile industry: Kyoto (0.42) and Aichi (4.96).[2] (Note that they have almost the same winter temperature: 5.5°C vs. 5.6°C.) It can be observed that the IIP increases much sharper in Aichi than in Kyoto in response to an oil demand shock triggered by an increase in global economic activity. This result is intuitive because the shock would raise the exports of cars from Japan and thus would affect a region that specializes more in the automobile industry like Aichi.

Although the observations from Figure 1 discussed above may seem informative, they are insufficient, or may even be misleading, to draw conclusions about the effects of oil shocks and regional heterogeneity because the differences in the effects of oil shocks across regions depends on not just one but many factors.

The regression in Tables 1 and 2 helps us deal with this multiple-factor problem. Here the contributions of shock in the variances of the price level and output are regressed on a number of factors that would be relevant.

[2] This prefecture is famous for being the hometown of Toyota, where the headquarter and several car factories of Toyota as well as many firms trading with Toyota are located.

In Table 1, we can see that the degree of specialization in the automobile industry of a region significantly positively affects the response of output of that region to oil demand shocks coming from global economic activity. This is consistent with the observation discussed above in Figure 1. We also observe that this response of output is significantly negatively related to winter temperature and value added per person in industry, while it is significantly positively related to the amount of fuel consumption per person in a region.

Table 2 shows that almost all factors significantly affects the response of the price level of a region to oil market specific demand shocks. The results on the two factors winter temperature, cars owned per person and fuel consumption per person are all consistent with the observations made above in Figure 1.[3] In addition, it is interesting to observe that value added per person in industry and in agriculture are both significant and have negative coefficients. This last result may appear puzzling but can be explained by noting that a region with higher value added per person in industry and in/or agriculture is less dependent on other regions for industrial and/or agricultural goods, and its price level will be less affected by changes in the transportations cost required to import industrial and/or agricultural goods which are closely related to fluctuations in the oil price.

5. Concluding Remarks

We have asked the question: How the effects of oil shocks across different regions in a country are related to the heterogeneity between those regions. We have utilized the data of Japan and have adopted a VAR with block exogeneity to answer the question. We find that the regional heterogeneity in natural and socio-economic environment does affect the way the regional economies respond to oil shocks. More specifically, a region with colder winter, higher number of cars owned per person, more fuel consumption, or lower value added per person in industry and agriculture has the price level affected more by oil market specific shocks. A region that specializes more in the automobile industry has output more influenced by oil demand shocks coming from global economic activity.

[3] The *negative* coefficient implies that the lower the temperature in winter in a region, the *more* its price level is affected by oil market specific demand shocks.

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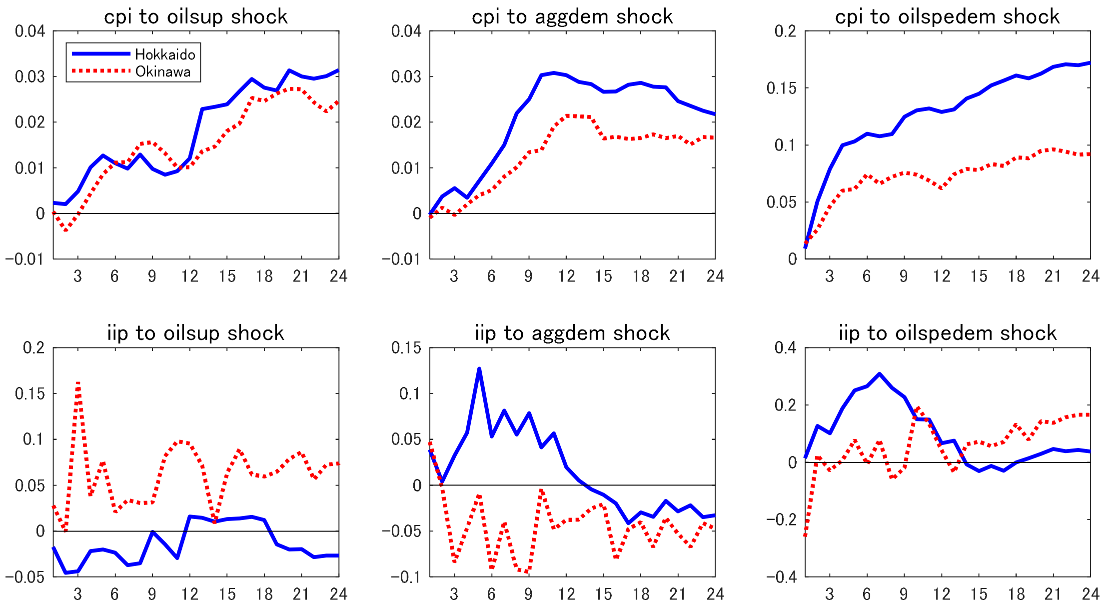
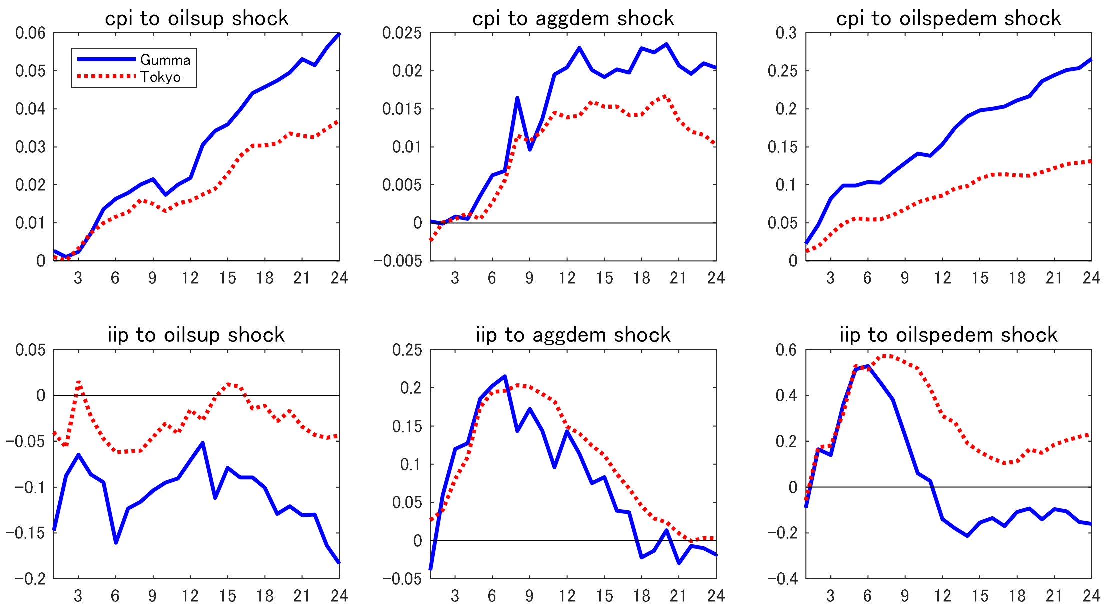
Figure 1: Comparisons of IRFs between pairs of prefectures with different characteristics

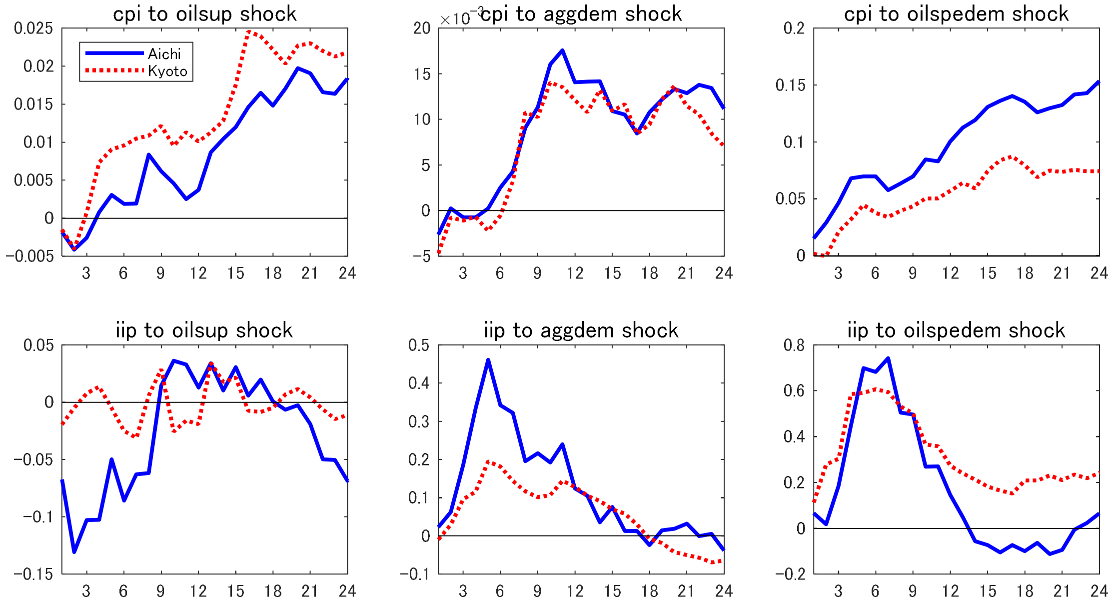
Case 1: Difference in temperature in winter: Hokkaido (-2.5°C) vs. Okinawa (17.6°C)



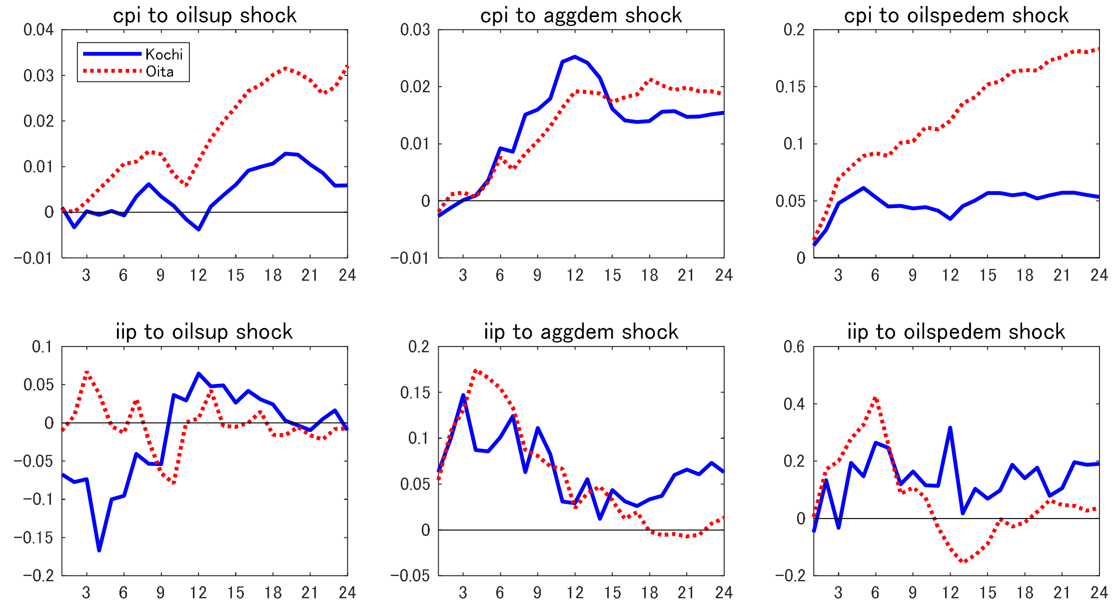
Case 2: Difference in cars owned per person: Tokyo (0.32) vs. Gunma (0.82)



Case 3: Difference in the coefficient of specialization in the automobile industry: Kyoto (0.42) vs. Aichi (4.96) (both with almost the same winter temperature: 5.5 vs. 5.6)



Case 4: Difference in consumption of fuel per person: Oita (12.82kl of crude oil) vs. Kochi (0.72 kl of crude oil) (both with almost the same winter temperature: 7.2 vs. 7.4)



Notes: Estimated using the VARX model in Section 2 and data in Section 3. Results of the IRFs shown here are the median or the error bands obtained by a bootstrapping method. Notations: *oilsup* shock: oil supply shock, *aggdem* shock: oil demand shock from global economic activity, and *oilspedem* shock: oil market specific demand shock. The sizes of these shocks are defined such that an *oilsup* shock raises oil production by one percent, an *aggdem* shock raises global economic activity by one percent, and an *oilspedem* shock raises the nominal oil price by one percent.

Table 1: The relations between the effects of oil shocks on regional output and various regional natural and socio-economic indicators

Dependent variable: Contribution of oil demand shock from global economic activity to variance of IIP at the one-year horizon				
Independent variable	Coefficient	Std. Error	t-Statistic	Prob.
TEMP_WINTER	-0.45	0.21	-2.20	0.034
SPECCOEF_AUTO	2.05	0.75	2.71	0.010
LOG(FUEL_CONSUMPC)	0.67	0.32	2.13	0.039
LOG(AGRIVALADDPC)	-0.24	0.91	-0.27	0.791
LOG(INDUSTRYVALADDPC)	-4.06	2.24	-1.81	0.078
LOG(SERVICEVALADDPC)	1.86	4.34	0.43	0.670
C	9.37	3.53	2.66	0.011
Number of observations: 47	Adjusted R-squared: 0.16			

Notes: OLS estimates using with data on the dependent variable from the variance decomposition of the VARX model, and data on independent variables described in Section 3. Notations: TEMP_WINTER: temperature in winter, SPECCOEF_AUTO: coefficient of specialization in the automobile industry, FUEL_CONSUMPC: fuel consumption per person, AGRIVALADDPC: value added per person in agriculture, INDUSTRYVALADDPC: value added per person in industry, SERVICEVALADDPC: value added per person in services, C: the constant term.

Table 2: The relations between the effects of oil shocks on the regional price level and various regional natural and socio-economic indicators

Dependent variable: Contribution of oil market specific demand shock to variance of CPI at the one-year horizon				
Independent variable	Coefficient	Std. Error	t-Statistic	Prob.
TEMP_WINTER	-0.93	0.18	-5.08	0.000
CARS_PC	42.28	11.20	3.78	0.001
LOG(FUEL_CONSUMPC)	0.50	0.29	1.73	0.091
LOG(AGRIVALADDPC)	-3.20	1.50	-2.14	0.039
LOG(INDUSTRYVALADDPC)	-5.09	2.27	-2.24	0.031
LOG(SERVICEVALADDPC)	5.22	3.75	1.39	0.172
C	-24.34	11.87	-2.05	0.047
Number of observations: 47	Adjusted R-squared: 0.49			

Notes: OLS estimates using with data on the dependent variable from the variance decomposition of the VARX model, and data on independent variables described in Section 3. Notations: TEMP_WINTER: temperature in winter, CARS_PC: number of cars owned per person, FUEL_CONSUMPC: fuel consumption per person, AGRIVALADDPC: value added per person in agriculture, INDUSTRYVALADDPC: value added per person in industry, SERVICEVALADDPC: value added per person in services, C: the constant term.

Appendix: Description and sources of regional data of Japan

Variable	Description	Data source & calculation
AGRIVALADDPC	Value added per person in agriculture	SNA, the Economic and Social Research Institute (ESRI), Cabinet Office of Japan. Average of 2001-2014
CARS_PC	Number of cars owned per person	Automobile Inspection & Registration Information Association; Statistics Bureau, Ministry of Internal Affairs and Communications of Japan. Average of 2001-2014.
FUEL_CONSUMPC	Fuel consumption per person	METI, Yearbook of the Current Survey of Energy Consumption (YCSEC); Statistics Bureau, Ministry of Internal Affairs and Communications of Japan. Average of 2008-2016.
INDUSTRYVALADDPC	Value added per person in industry	SNA, ESRI Average of 2001-2014.
SERVICEVALADDPC	Value added per person in services	SNA, ESRI Average of 2001-2014.
SPECCOEF_AUTO	Coefficient of specialization in automobile industry	Taken from Nakata and Vu (2018)
TEMP_ WINTER	Average temperature in winter (December-February)	Japan Meteorological Agency. Average of 1980-2011.