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Dynamic relationships among changes in prices of beef, pork, and chicken in Japan: A Bayesian approach

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ABSTRACT

In this paper, we investigate the interdependence among changes in the prices of beef, pork, and chicken in Japan using a time-varying coefficient vector autoregressive model. Our empirical analysis using monthly data from January 1990 to March 2014 shows that changes in beef prices have long-term influences on changes in pork and chicken prices. Moreover, current changes in the prices of beef, pork, and chicken are closely related to changes in their prices in the preceding two months. Additionally, we do not find that the bovine spongiform encephalopathy outbreak announced by the Japanese government in September 2001 had a long-term influence on the dynamic relationships among changes in the prices of beef, pork, and chicken in Japan.

1. Introduction

Changes in various meat prices may be closely related to each other. However, the details of such relationships are not always obvious. Understanding the interdependence among meat prices is important from the perspective of both consumers and producers because such information is an essential part of the consumption schedule and can signal to firms that production should be adjusted. For example, suppose that there is a strongly positive correlation between the prices of beef and pork, but a weak correlation between the prices of beef and chicken. If the price of beef rises, then households will expect the price of pork to rise as well; hence, the demand for chicken, which has become relatively cheap, may increase simultaneously. Therefore, firms will increase chicken stocks in preparation for increased demand for chicken. Understanding the relationship between meat prices in this manner is beneficial to both households and firms.

In this study, we investigate what types of interdependence exist among changes in the prices of beef, pork, and chicken. Specifically, we focus on the case of Japan, where beef, pork, and chicken are the three major meats consumed by households, and consider these meat prices within the context of a dynamic modeling framework. We use a Bayesian vector autoregressive (VAR) model to analyze the dynamic relationships among fresh meat prices.

Earlier studies were conducted on the relationships among meat prices based on a conventional VAR modeling approach. For example [1], analyzed the relationships among Australian beef prices at the farm, wholesale, and retail levels and found that all three prices were co-integrated [2]. examined Danish meat prices and quantity transmissions using data from Danish pork, chicken, and beef markets. Their main results suggested that pork, chicken, and beef were close substitutes in Denmark [3]. investigated the relationships among the prices of broilers, cattle, ducks, and hogs in Taiwan. The results indicated that a bidirectional relationship existed between hog and broiler prices, and that a unidirectional relationship existed from duck to hog prices.

A conventional VAR modeling approach is useful for analyzing relationships within vector time series (see Ref. [4]. However, conventional VAR models can only be applied to stationary time series. Moreover, in a conventional VAR modeling approach, the coefficients in the models are considered as constant parameters despite the use of long-term time-series data. Although this reflects the assumption of invariability in the model structure, the assumption that there are no structural changes is clearly unrealistic when the model covers a period of several decades. Thus, much of the previous research may not be based on an appropriate dynamic framework. In fact [5], confirmed the existence of structural changes by examining structural breaks in the retail–farm price relationship in the Japanese pork market. Additionally [6], estimated structural changes in the relationship between beef and pork prices in the United States and confirmed the importance of allowing for structural changes in the analysis of price relationships.

[7] developed a Bayesian method based on a VAR model with

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time-varying coefficients (TVC-VAR) for analyzing a time series that is non-stationary in covariance. The TVC-VAR model can be used to explain the dynamic relationships between all variates in a vector time series with structural changes (see Ref. [8]. In the present study, we apply the Bayesian TVC-VAR modeling approach to the empirical analysis of the dynamic relationships among changes in the prices of beef, pork, and chicken in Japan, which is a subject that has not been addressed in previous studies. Our empirical analysis using monthly data from January 1990 to March 2014 shows that current changes in the prices of beef, pork, and chicken are closely related to changes in their prices in the preceding two months. Additionally, we do not find that the bovine spongiform encephalopathy (BSE) outbreak announced by the Japanese government in September 2001 had a long-term influence on the dynamic relationships among changes in the prices of beef, pork, and chicken in Japan.

The remainder of this paper is organized as follows: In Section 2, we explain the set-up of the model. In Section 3, we present the parameter estimation algorithm. We present the main results of our empirical analysis in Section 4. We present concluding remarks in Section 5.

2. Set-up of the model

We consider a set of monthly data containing the seasonally adjusted time series z_{n1}, z_{n2}, and z_{n3}, which express the prices of beef, pork, and chicken, respectively, where n is the n-th period. Then, we calculate the 3-month-ahead growth rates as follows:

$$r_{ni} = \frac{z_{ni} - z_{(n-3)i}}{z_{(n-3)i}} \approx \log z_{ni} - \log z_{(n-3)i} \quad (i = 1, 2, 3). \tag{1}$$

In (1), we assume that the time series r_{ni} ($i = 1, 2, 3$) are stationary in mean and that their means are $\mathrm{E}\{r_{ni}\} = \mu_i$ ($i = 1, 2, 3$), respectively. Thus, we can estimate μ_i ($i = 1, 2, 3$) using the sample means $\widehat{\mu}_i$ ($i = 1, 2, 3$) for r_{ni} ($i = 1, 2, 3$), respectively, and then express the 3-variate time series composed of the growth rates of beef, pork, and chicken prices as $y_n = (y_{n1}, y_{n2}, y_{n3})^{\mathrm{T}}$ based on the definition of $y_{ni} = r_{ni} - \widehat{\mu}_i$ ($i = 1, 2, 3$). We consider the TVC-VAR model for the vector time series y_n as follows:

$$y_n = \sum_{\ell=1}^{p} A_\ell(n) y_{n-\ell} + u_n, \tag{2}$$

where p is the model order and $A_\ell(n)$ ($\ell = 1, 2, \ldots, p$) are time-varying coefficient matrices for each lag value ℓ at time n. In (2), u_n is a 3-variate Gaussian white noise sequence with zero mean and covariance matrix $\Sigma(n)$. We assume that u_n and $y_{n-\ell}$ are mutually independent for $\ell > 0$.

To estimate the parameters of the TVC-VAR model in (2) in a more efficient manner, we construct a model that includes a simultaneous response in the form

$$y_n = \sum_{\ell=0}^{L} B_\ell(n) y_{n-\ell} + w_n, \tag{3}$$

where $w_n = (w_{n1}, w_{n2}, w_{n3})^{\mathrm{T}}$ is a 3-variate Gaussian white noise sequence with zero mean and covariance matrix $W = \mathrm{diag}(\sigma_1^2, \sigma_2^2, \sigma_3^2)$. The matrices $B_\ell(n)$ ($\ell = 0, 1, \ldots, L$) are coefficients defined as follows:

$$B_0(n) = \begin{bmatrix} 0 & 0 & 0 \\ b_{210}(n) & 0 & 0 \\ b_{310}(n) & b_{320}(n) & 0 \end{bmatrix},$$

$$B_\ell(n) = \begin{bmatrix} b_{11\ell}(n) & b_{12\ell}(n) & b_{13\ell}(n) \\ b_{21\ell}(n) & b_{22\ell}(n) & b_{23\ell}(n) \\ b_{31\ell}(n) & b_{32\ell}(n) & b_{33\ell}(n) \end{bmatrix}, \quad (\ell = 1, 2, \ldots, L).$$

$B_0(n)$ is called a simultaneous response matrix. For each element of y_n, the model in (3) can be rewritten as follows:

$$y_{n1} = \sum_{j=1}^{3} \sum_{\ell=1}^{L} b_{1j\ell}(n) y_{(n-\ell)j} + w_{n1}, \quad w_{n1} \sim \mathrm{N}(0, \sigma_1^2) \tag{4}$$

$$y_{n2} = b_{210}(n) y_{n1} + \sum_{j=1}^{3} \sum_{\ell=1}^{L} b_{2j\ell}(n) y_{(n-\ell)j} + w_{n2}, \quad w_{n2} \sim \mathrm{N}(0, \sigma_2^2) \tag{5}$$

$$y_{n3} = \sum_{j=1}^{2} b_{3j0}(n) y_{nj} + \sum_{j=1}^{3} \sum_{\ell=1}^{L} b_{3j\ell}(n) y_{(n-\ell)j} + w_{n3}, \quad w_{n3} \sim \mathrm{N}(0, \sigma_3^2). \tag{6}$$

we can assume that w_{n1}, w_{n2}, and w_{n3} are independent of each other. Thus, we can estimate parameters for each model in (4)–(6) separately to improve the efficiency of parameter estimation. This is the first advantage of using a form of the TVC-VAR model with a simultaneous response.

To estimate the time-varying coefficients, we apply a Bayesian method using smoothness priors of order 1 for the non-zero elements in the matrices $B_\ell(n)$ ($\ell = 0, 1, \ldots, L$); that is, we introduce a set of smoothness priors of order 1 in the form

$$b_{ij\ell}(n) - b_{ij\ell}(n-1) = v_{ij\ell}(n), \tag{7}$$

where $v_{ij\ell}(n)$ is a Gaussian white noise sequence with zero mean and unknown variance τ_i^2. We can confirm that the models in (2) and (3) are related by

$$A_\ell(n) = (I - B_0(n))^{-1} B_\ell(n), \quad (\ell = 1, 2, \ldots, L) \tag{8}$$

$$\Sigma(n) = (I - B_0(n))^{-1} W (I - B_0(n))^{-\mathrm{T}}. \tag{9}$$

Therefore, if the parameters in the model in (3) are estimated, we can obtain those in the model in (2) using (8) and (9).

When the values for $A_\ell(n)$ and $\Sigma(n)$ are given by the estimates, we can obtain the time-varying cross-spectrum, power contribution, and covariance function for the time series using the method proposed by Ref. [7]. In particular, the time-varying power contribution and covariance function assist in explaining the dynamic relationship between every variate in the vector time series.

The time-varying covariance (TVCV) shows instantaneous covariance between the variables, and the time-varying power contribution of variable j to variable i expresses the degree of contribution of innovation in the j-th component model to the power of the i-th component model at a frequency. Thus, the TVCV indicates dynamics in the relation between the variables in the time domain, and the time-varying power contribution indicates the dynamics in the relation between the variables in the frequency domain.

3. Parameter estimation

3.1. Estimating the time-varying coefficients

Now, we set

$$\begin{aligned}
x_n^{(1)} &= [b_{111}(n)\ b_{121}(n)\ b_{131}(n) \cdots b_{11L}(n)\ b_{12L}(n)\ b_{13L}(n)], \\
x_n^{(2)} &= [b_{210}(n)\ b_{211}(n)\ b_{221}(n)\ b_{231}(n) \cdots b_{21L}(n)\ b_{22L}(n)\ b_{23L}(n)], \\
x_n^{(3)} &= [b_{310}(n)\ b_{320}(n)\ b_{311}(n)\ b_{321}(n)\ b_{331}(n) \cdots b_{31L}(n)\ b_{32L}(n)\ b_{33L}(n)], \\
v_n^{(1)} &= [v_{111}(n)\ v_{121}(n)\ v_{131}(n) \cdots v_{11L}(n)\ v_{12L}(n)\ v_{13L}(n)], \\
v_n^{(2)} &= [v_{210}(n)\ v_{211}(n)\ v_{221}(n)\ v_{231}(n) \cdots v_{21L}(n)\ v_{22L}(n)\ v_{23L}(n)], \\
v_n^{(3)} &= [v_{310}(n)\ v_{320}(n)\ v_{311}(n)\ v_{321}(n)\ v_{331}(n) \cdots v_{31L}(n)\ v_{32L}(n)\ v_{33L}(n)], \\
H_{n1} &= \left[y_{(n-1)1}\ y_{(n-1)2}\ y_{(n-1)3} \cdots y_{(n-L)1}\ y_{(n-L)2}\ y_{(n-L)3}\right], \\
H_{n2} &= \left[y_{n1}\ y_{(n-1)1}\ y_{(n-1)2}\ y_{(n-1)3} \cdots y_{(n-L)1}\ y_{(n-L)2}\ y_{(n-L)3}\right], \\
H_{n3} &= \left[y_{n1}\ y_{n2}\ y_{(n-1)1}\ y_{(n-1)2}\ y_{(n-1)3} \cdots y_{(n-L)1}\ y_{(n-L)2}\ y_{(n-L)3}\right]
\end{aligned}$$

and

$$G_i = F_i = I_{3L+i-1}, \quad Q_i = \tau_i^2 I_{3L+i-1}, \quad R_i = \sigma_i^2 \quad (i = 1, 2, 3),$$

where I_{3L+i-1} is the identity matrix of size $3L+i-1$. Next, together with (7), we can express one of the models in (4)–(6) using the following state-space model:

$$x_n^{(i)} = F_i x_{n-1}^{(i)} + G_i v_n^{(i)}, \tag{10}$$

$$y_{ni} = H_{ni} x_n^{(i)} + w_{ni}, \quad (i = 1, 2, 3). \tag{11}$$

In the state-space model comprising (10) and (11), the time-varying coefficients are included in the state vector $x_n^{(i)}$. Thus, we can obtain their estimates from the estimate of $x_n^{(i)}$. Moreover, we can estimate the parameters σ_i^2 and τ_i^2, which are called hyperparameters, using the maximum-likelihood method.

Let $x_0^{(i)}$ denote the initial value of the state $x_n^{(i)}$ and let $Y_m = \{y_1, y_2, \ldots, y_m\}$ denote a set of observations for the time series y_n up to the time point m. We assume that $x_0^{(i)} \sim \mathrm{N}(x_{0|0}^{(i)}, V_{0|0}^{(i)})$. It is well known that the distribution $f(x_n^{(i)}|Y_m)$ for the state $x_n^{(i)}$ conditional on Y_m is Gaussian. Therefore, it is only necessary to obtain the mean $x_{n|m}^{(i)}$ and covariance matrix $V_{n|m}^{(i)}$ of $x_n^{(i)}$ with respect to $f(x_n^{(i)}|Y_m)$.

When the values of L, σ_i^2, and τ_i^2, the initial distribution $\mathrm{N}(x_{0|0}^{(i)}, \mathrm{V}_{0|0}^{(i)})$, and a set of observations up to the period N are given, we can obtain the estimates for the state $x_n^{(i)}$ using the well-known Kalman filter (for $n = 1, 2, \ldots, N$) and fixed-interval smoothing (for $n = N-1, N-2, \ldots, 1$) recursively as follows (see Refs. [9,10]:

[Kalman filter]

$$\begin{aligned}
x_{n|n-1}^{(i)} &= F_i x_{n-1|n-1}^{(i)}, \\
V_{n|n-1}^{(i)} &= F_i V_{n-1|n-1}^{(i)} F_i^{\mathrm{T}} + G_i Q_i G_i^{\mathrm{t}}, \\
K_{ni} &= V_{n|n-1}^{(i)} H_{ni}^{\mathrm{T}} (H_{ni} V_{n|n-1}^{(i)} H_{ni}^{\mathrm{T}} + R_i)^{-1}, \\
x_{n|n}^{(i)} &= x_{n|n-1}^{(i)} + K_{ni}(y_{ni} - H_{ni} x_{n|n-1}^{(i)}), \\
V_{n|n}^{(i)} &= (I_{3L+i-1} - K_{ni} H_{ni}) V_{n|n-1}^{(i)}.
\end{aligned}$$

[Fixed-interval smoothing]

$$\begin{aligned}
A_{ni} &= V_{n|n}^{(i)} F_i^{\mathrm{T}} (V_{n+1|n}^{(i)})^{-1}, \\
x_{n|N}^{(i)} &= x_{n|n}^{(i)} + A_{ni}(x_{n+1|N}^{(i)} - x_{n+1|n}^{(i)}), \\
V_{n|N}^{(i)} &= V_{n|n}^{(i)} + A_{ni}(V_{n+1|N}^{(i)} - V_{n+1|n}^{(i)}) A_{ni}^{\mathrm{T}}.
\end{aligned}$$

I denotes the identity matrix.

The posterior distribution of $x_n^{(i)}$ can then be given by $\mathrm{N}(x_{n|N}^{(i)}, V_{n|N}^{(i)})$ and we can obtain the estimates for the time-varying coefficients because the state-space model described by (10) and (11) incorporates the coefficients in the state vector $x_n^{(i)}$.

3.2. Estimating the constant parameters

Let $Y_{(n-1)} = \{y_1, y_2, \ldots, y_{(n-1)}\}$ be the set of observations for the time series y_n up to the time point $n-1$, where Y_0 is an empty set. When the value of model order L and all time-series data Y_N are given, a likelihood function of the hyperparameters σ_1^2, τ_1^2, σ_2^2, τ_2^2, σ_3^2 and τ_3^2 is defined approximately as

$$\begin{aligned}
f(Y_N|\sigma_1^2, \tau_1^2, \sigma_2^2, \tau_2^2, \sigma_3^2, \tau_3^2) &= \prod_{n=1}^{N} f_n^{(1)}(y_{n1}|Y_{(n-1)}; \sigma_1^2, \tau_1^2) \\
&\times f_n^{(2)}(y_{n2}|y_{n1}, Y_{(n-1)}; \sigma_2^2, \tau_2^2) f_n^{(3)}(y_{n3}|y_{n1}, y_{n2}, Y_{(n-1)}; \sigma_3^2, \tau_3^2),
\end{aligned}$$

where $f_n^{(1)}(y_{n1}|Y_{(n-1)}; \sigma_1^2, \tau_1^2)$ is the conditional density of y_{n1} given the past observations $Y_{(n-1)}$, together with the values of σ_1^2 and τ_1^2, and so on. As shown by Ref. [10]; using the Kalman filter, the conditional densities are normal densities given by

$$\begin{aligned}
f_n^{(1)}(y_{n1}|Y_{(n-1)}; \sigma_1^2, \tau_1^2) &= \frac{1}{\sqrt{2\pi d_{n|n-1}^{(1)}}} \exp\left\{ -\frac{(y_{n1} - \hat{y}_{n|n-1}^{(1)})^2}{2d_{n|n-1}^{(1)}} \right\}, \\
f_n^{(2)}(y_{n2}|y_{n1}, Y_{(n-1)}; \sigma_2^2, \tau_2^2) &= \frac{1}{\sqrt{2\pi d_{n|n-1}^{(2)}}} \exp\left\{ -\frac{(y_{n2} - \hat{y}_{n|n-1}^{(2)})^2}{2d_{n|n-1}^{(2)}} \right\}, \\
f_n^{(3)}(y_{n3}|y_{n1}, y_{n2}, Y_{(n-1)}; \sigma_3^2, \tau_3^2) &= \frac{1}{\sqrt{2\pi d_{n|n-1}^{(3)}}} \exp\left\{ -\frac{(y_{n3} - \hat{y}_{n|n-1}^{(3)})^2}{2d_{n|n-1}^{(3)}} \right\},
\end{aligned}$$

where $\hat{y}_{n|n-1}^{(i)}$ is the mean for the one-step-ahead prediction of y_{ni} and $d_{n|n-1}^{(i)}$ is the variance of the predictive error, with each given, respectively, by

$$\hat{y}_{n|n-1}^{(i)} = H_{ni} x_{n|n-1}^{(i)}, \quad d_{n|n-1}^{(i)} = H_{ni} V_{n|n-1}^{(i)} H_{ni}^{\mathrm{t}} + \sigma_i^2, \quad (i = 1, 2, 3).$$

By taking the logarithm of $f(Y_N|\sigma_1^2, \tau_1^2, \sigma_2^2, \tau_2^2, \sigma_3^2, \tau_3^2)$, we obtain the log-likelihood (LL) as

$$\begin{aligned}
\ell(\sigma_1^2, \tau_1^2, \sigma_2^2, \tau_2^2, \sigma_3^2, \tau_3^2) &= \log f(Y_N|\sigma_1^2, \tau_1^2, \sigma_2^2, \tau_2^2, \sigma_3^2, \tau_3^2) \\
&= \ell_1(\sigma_1^2, \tau_1^2) + \ell_2(\sigma_2^2, \tau_2^2) + \ell_3(\sigma_3^2, \tau_3^2),
\end{aligned}$$

where $\ell_1(\sigma_1^2, \tau_1^2)$, $\ell_2(\sigma_2^2, \tau_2^2)$, and $\ell_3(\sigma_3^2, \tau_3^2)$ are the partial LL functions, which are given by

$$\begin{aligned}
\ell_1(\sigma_1^2, \tau_1^2) &= \sum_{n=1}^{N} \log f_n^{(1)}(y_{n1}|Y_{(n-1)}; \sigma_1^2, \tau_1^2), \\
\ell_2(\sigma_2^2, \tau_2^2) &= \sum_{n=1}^{N} \log f_n^{(2)}(y_{n2}|y_{n1}, Y_{(n-1)}; \sigma_2^2, \tau_2^2), \\
\ell_3(\sigma_3^2, \tau_3^2) &= \sum_{n=1}^{N} \log f_n^{(3)}(y_{n3}|y_{n1}, y_{n2}, Y_{(n-1)}; \sigma_3^2, \tau_3^2).
\end{aligned}$$

Thus, we can obtain the estimates of the hyperparameters using the maximum-likelihood method, that is, we obtain the estimates for the hyperparameters σ_1^2, τ_1^2 by maximizing $\ell_1(\sigma_1^2, \tau_1^2)$, and similarly for the other hyperparameters.

Theoretically, the value of model order L should be determined using the minimum Akaike information criterion (AIC) method [11]. However, we use a vague distribution to set $\mathrm{N}(x_{0|0}^{(i)}, V_{0|0}^{(i)})$ using $x_{0|0}^{(i)} = 0$ and $V_{0|0}^{(i)} = \delta I$ for $i = 1, 2, 3$, where δ is a sufficiently large positive number. In this case, we can also determine the values of L using the maximum-likelihood method because the number of hyperparameters in the model is identical for different values of L.

3.3. Checking the instantaneous stationarity

We assume that the time series y_n is non-stationary in covariance globally, but stationary locally. Thus, the TVC-VAR model constructed is stationary instantaneously; that is, it may be non-stationary overall, but stationary at each time point n; hence, the covariance, cross-spectrum, and power contribution can be defined and estimated. Therefore, it is necessary to check the instantaneous stationarity for model (2).

For a VAR model of three-dimensional time series y_n defined as

$$y_n = \sum_{\ell=1}^{p} A_\ell y_{n-\ell} + U_n, \tag{12}$$

we can check stationarity by observing the roots of the equation for z:

$$\det\left(I_3 - \sum_{\ell=1}^{p} A_\ell z^\ell \right), \tag{13}$$

where I_3 is a three-order unit matrix and $\det(X)$ denotes the determinant of matrix X. If all roots of (13) lie outside the unit circle (see, e.g. Ref. [12], then the model in (12) is regarded as a stationary VAR model. However, for a large value of p, such a method should not be applied easily.

[13] proposed a method to check stationarity for a VAR process as follows: For the VAR model (12) (with non-singular matrix A_p) to be stationary, all eigenvalues of the following matrix must lie inside the unit circle:

$$\begin{bmatrix} A_1 & A_2 & \dots & A_p \\ I_3 & & 0 & 0 \\ & \ddots & & \vdots \\ 0 & & I_3 & 0 \end{bmatrix}.$$

As the method mentioned above can be applied easily, we apply it to check the instantaneous stationarity of model (2). For a given value of n, we compute the eigenvalues of the matrix:

$$\begin{bmatrix} \widehat{A}_1(n) & \widehat{A}_2(n) & \dots & \widehat{A}_p(n) \\ I_3 & & 0 & 0 \\ & \ddots & & \vdots \\ 0 & & I_3 & 0 \end{bmatrix}$$

, where $\widehat{A}_\ell(n)$ is an estimate for the matrix $A_\ell(n)$. We can see that the TVC-VAR model is stationary at time n if the largest absolute value of the eigenvalues is less than one. Hence, the model is stationary instantaneously when it is stationary for $n = 1, 2, \dots, N$.

4. Empirical investigation

4.1. Data

We applied the TVC-VAR modeling approach to Japanese monthly data on fresh meat prices (beef, pork, and chicken) from January 1990 to March 2014. The data are available from the Agriculture & Livestock Industries Corporation (ALIC), Japan. Specifically, we obtained data from the ALIC website on the monthly consumption quantity and total value of various types of fresh meat for Japanese households. Then, we calculated the prices using the ratio of total value to quantity consumed and used the results as the prices of beef (x_{n1}), pork (x_{n2}), and chicken (x_{n3}) with $n = 1, 2, \dots, 291$. Fig. 1 shows the original data for log x_{n1}, log x_{n2}, and log x_{n3}.

Fig. 1(a) shows that there is a conspicuous seasonal component in the data for log x_{n1}, and Fig. 1(b) shows that the data for log x_{n2} contains moderate seasonally variation. To obtain seasonally adjusted values of the prices, we decomposed each time series of the prices using the seasonal adjust model, which was introduced by Ref. [14]; pp. 201–206). For example, for the time series of the beef price, we considered the model as follows:

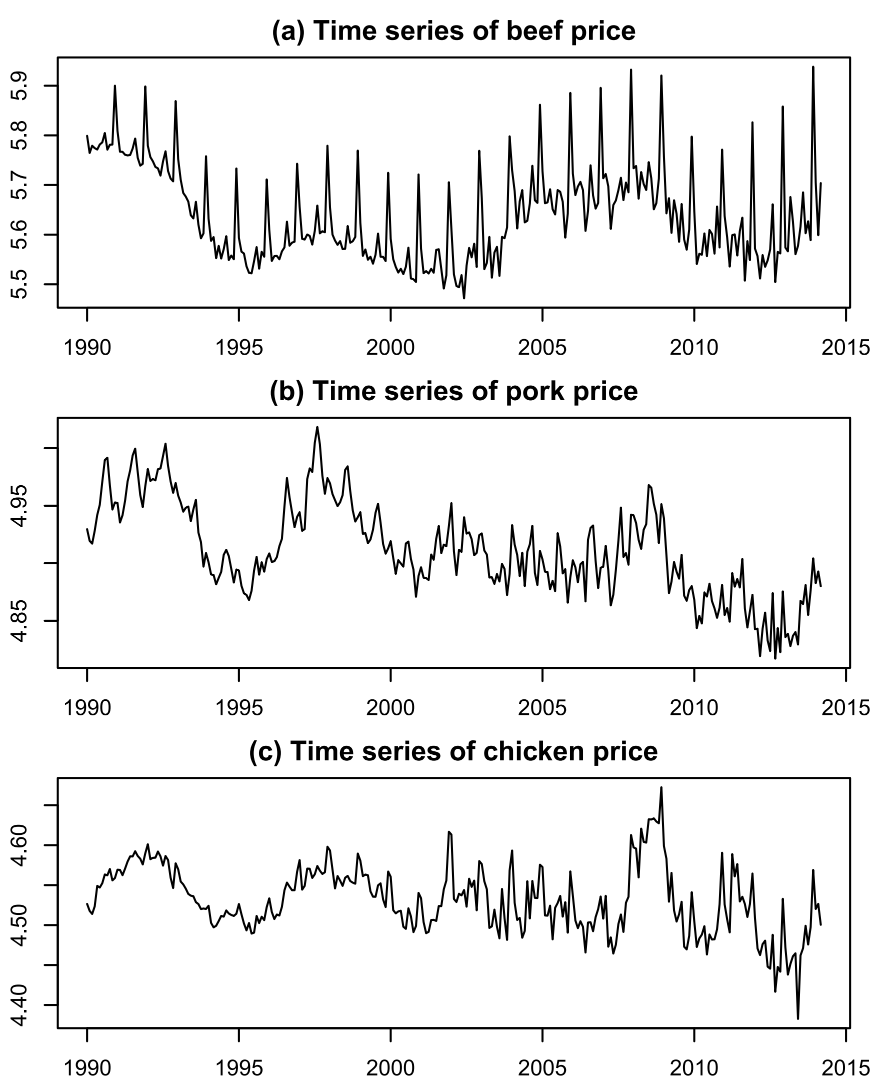

Fig. 1. Original time series for the prices of beef, pork, and chicken on a logarithmic scale (Jan. 1990 ~ Mar. 2014).

$X_{n1} = \log x_{n1} = t_n + s_n + p_n + w_n,$

where t_n, s_n, p_n, and w_n are the trend component, seasonal component, cyclical component, and observation noise, respectively. We omit the details in this paper; however, we obtained the estimates for each component, and then calculated the seasonally adjusted time series for the beef price using $\widehat{X_{n1}} = X_{n1} - \widehat{s_n}$, where $\widehat{s_n}$ denotes the estimate for the seasonal component. Clearly, $\widehat{X_{n1}}$ can be regarded as the seasonally adjusted time series of the beef price on a logarithmic scale; that is, in the notation in (1), we can consider that $\log z_{n1} = \widehat{X_{n1}}$. Note that we can obtain a similar seasonally adjusted time series of the price of pork $\log z_{n2}$ and that of chicken $\log z_{n3}$.

Fig. 2 shows seasonally adjusted time series of the prices of beef, pork, and chicken on a logarithmic scale.

Considering (1), we calculated the 3-month-ahead growth rates for the prices of beef (y_{n1}), pork (y_{n2}), and chicken (y_{n3}) from the data for $\log z_{n1}$, $\log z_{n2}$, and $\log z_{n3}$, respectively. Fig. 3 shows the 3-month-ahead growth rates for the prices of beef, pork, and chicken.

For the period from April 1990 to December 1999, the changes in the prices of beef, pork, and chicken were relatively stable. However, during the period from January 2000 to March 2014, there were large fluctuations. In particular, marked volatility can be observed in the beef price since the 2000s. The standard deviations of price changes for beef, pork, and chicken during the period from April 1990 to December 1999 were 1.63, 1.65, and 1.20, respectively. However, during the period from January 2000 to March 2014, the standard deviations of price changes for beef, pork, and chicken were 3.58, 2.00, and 2.48, respectively; that is, during the 1990s, changes in the pork price showed the highest dispersion. However, from the 2000s, this altered such that changes in the beef price showed the highest dispersion, whereas changes in the pork price showed the lowest dispersion.

This difference in the nature of fluctuations between the 1990s and 2000s suggests a structural change in meat prices in Japan. As mentioned above, the TVC-VAR model is an effective tool for analyzing time-series data with structural changes, whereas conventional VAR modeling with constant parameters is inadequate when there are structural changes.

4.2. Results and discussion

In this section, we describe how to determine the value of the model order (p). In theory, the value of p should be determined using the minimum AIC method (see Ref. [11]. However, we use a vague distribution of the initial state, which allows us to estimate p using the maximum-likelihood method. Table 1 presents the LL values for the Bayesian TVC-VAR model in (3), together with (7), for $p = 1, 2, \ldots, 15$.

As shown in Table 1, when $p = 8$, the LL takes its maximum value:

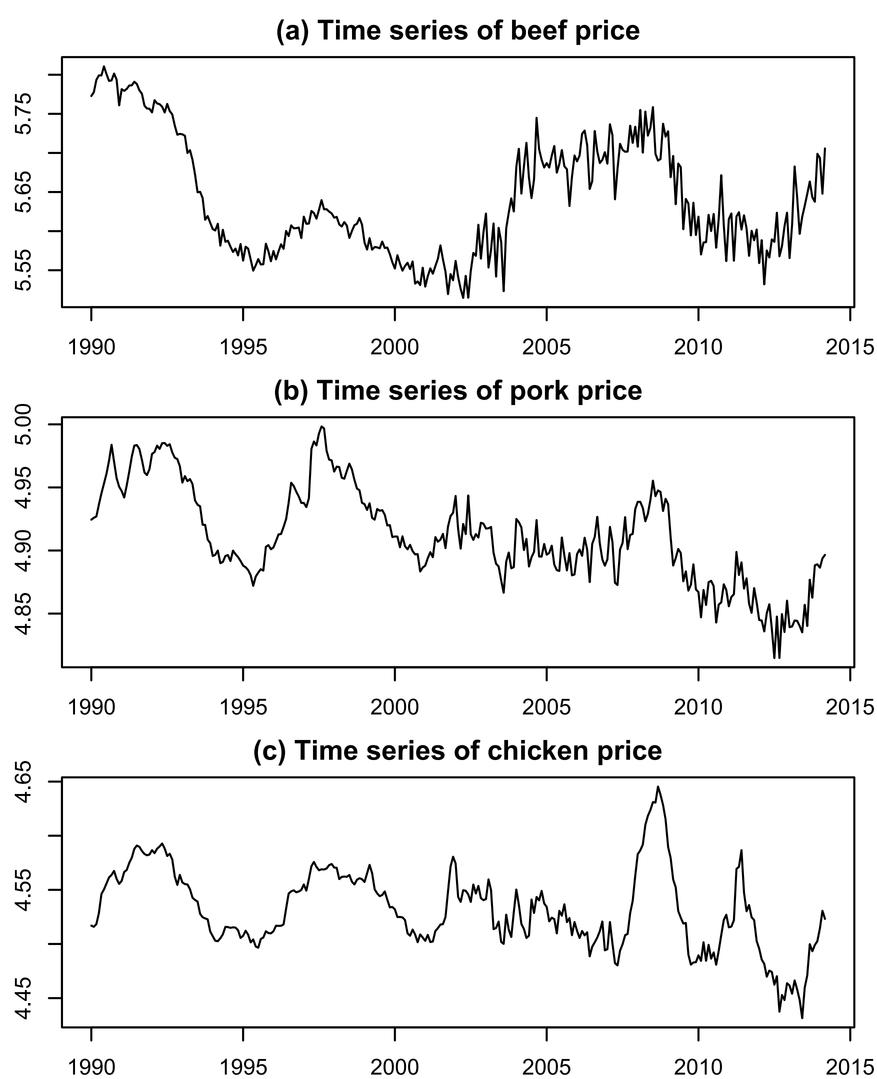

Fig. 2. Seasonally adjusted time series of the prices of beef, pork, and chicken on a logarithmic scale (Jan. 1990 ~ Mar. 2014).

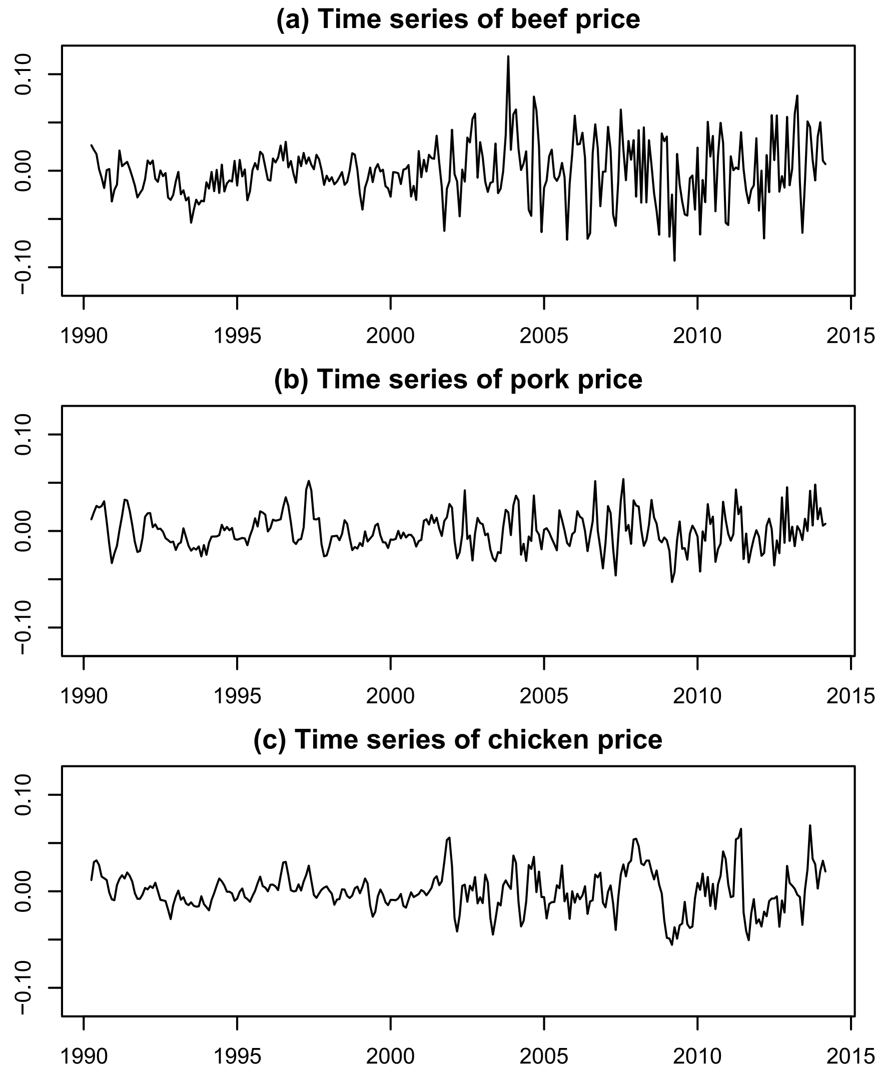

Fig. 3. Time series for the growth rates of the prices of beef, pork, and chicken (Apr. 1990 ~ Mar. 2014).

Table 1
Log-likelihood values for different values of the model order (p).

Model order	Log-likelihood
1	2260.89
2	2268.74
3	2315.01
4	2329.10
5	2334.17
6	2343.16
7	2343.86
8	2346.85
9	2343.39
10	2345.81
11	2346.37
12	2340.77
13	2334.37
14	2327.54
15	2323.60

2346.85. Therefore, we consider the model with $p = 8$.

Fig. 4 illustrates the estimated time-varying power contribution, which is also known as the relative noise contribution (RNC).

Regarding the common range of the vertical axis in Fig. 4, the maximum value is 1.3423 and the minimum value is 1.7475×10^{-8}. In Table 2, we summarize the meaning of the nine panels in Fig. 4.

To determine how the power contribution varies with frequency, we calculated the average on time. Fig. 5 shows the relationship between frequency and the power contribution in the time averaging value.

In Fig. 5, the horizontal axis represents frequency and the vertical axis represents the time-varying power contribution. Similarly to Fig. 5, we calculated the average of the power contribution on frequency. Fig. 6 shows the relationship between time and the power contribution in the frequency averaging value.

In Fig. 6, the horizontal axis represents time and the vertical axis represents the time-varying power contribution.

First, we focus on the panels on the diagonal line from the upper left to the lower right, that is, Fig. 4(a), (e), and (i). As expected, each meat price change has the most influence on itself. Moreover, Fig. 6 shows that the time-varying power contribution is consistently high throughout the analysis period. For example, looking at Fig. 4(a)–6(a), the time-varying power contribution is very large from the viewpoints of the frequency domain and time domain. Note that the duration of influence is short (long) in a high (low)-frequency domain. Therefore, we can interpret the data as indicating that a change in the beef price has an impact on itself, not only in the short term but also in the long term.

Moreover, Fig. 6(e) and (i) show that the time-varying power contribution has increased since 2003. This may be the effect of BSE that occurred in the United States in December 2003; that is, it is possible

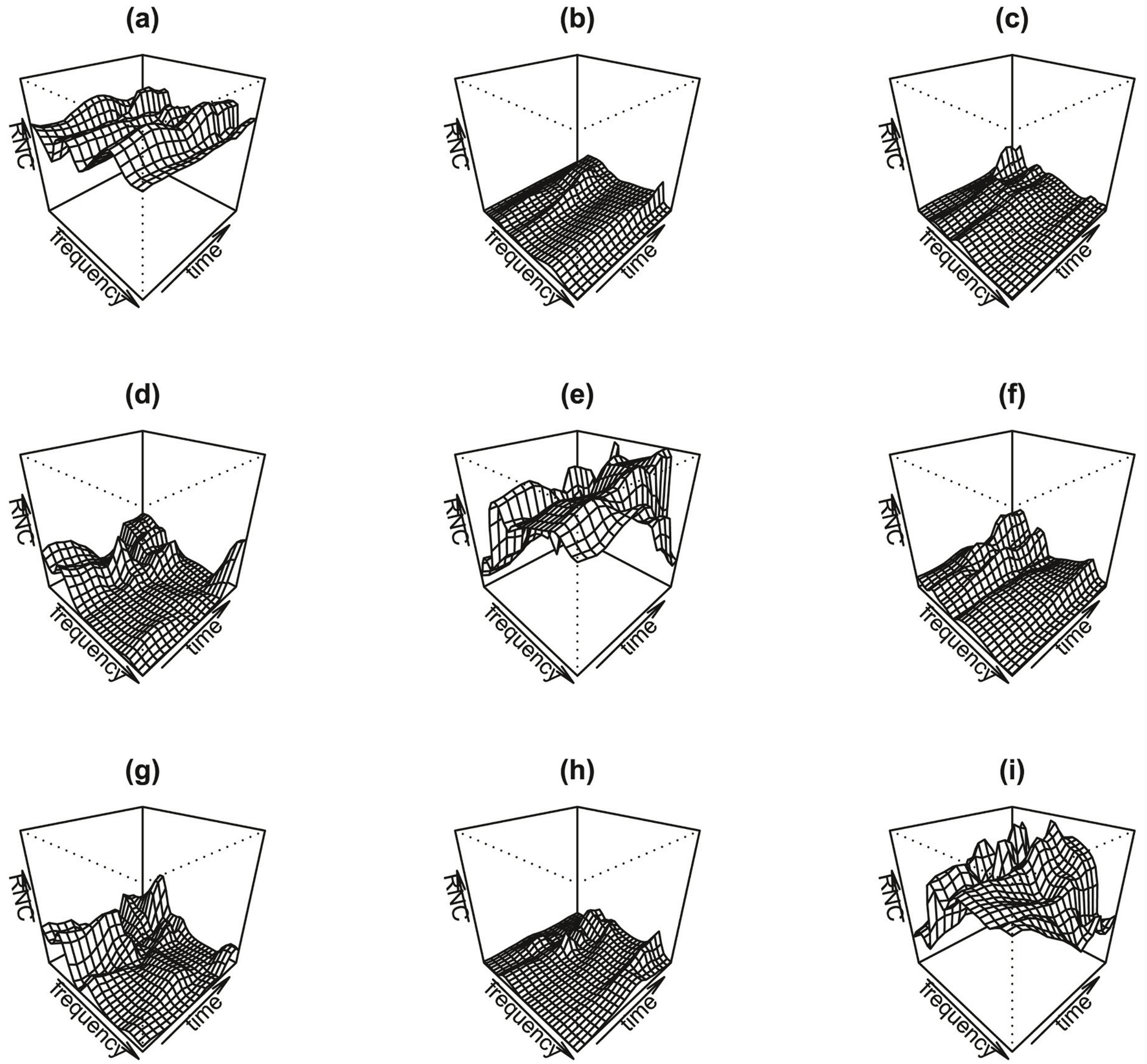

Fig. 4. Time-varying power contribution.

Table 2
Time-varying power contribution.

panel	meaning	range of RNC value (min, max)
(a)	the effect of changes in the beef price on itself	(2.0178×10^{-1}, 1.1851)
(b)	the effect of changes in the pork price on changes in the beef price	(1.7475×10^{-8}, 0.2849)
(c)	the effect of changes in the chicken price on changes in the beef price	(1.3170×10^{-7}, 0.3577)
(d)	the effect of changes in the beef price on changes in the pork price	(2.1847×10^{-7}, 0.5724)
(e)	the effect of changes in the pork price on itself	(5.3598×10^{-2}, 1.3336)
(f)	the effect of changes in the chicken price on changes in the pork price	(1.2112×10^{-4}, 0.4919)
(g)	the effect of changes in the beef price on changes in the chicken price	(4.9346×10^{-7}, 0.6359)
(h)	the effect of changes in the pork price on changes in the chicken price	(1.1470×10^{-5}, 0.2932)
(i)	the effect of changes in the chicken price on itself	(2.8961×10^{-1}, 1.3523)

that BSE caused consumer demand for meat to shift from beef to pork and chicken, and as a result, the contribution of pork and chicken increased.

Fig. 4(c) also shows relatively similar characteristics to Fig. 4(a). Specifically, a change in the chicken price has an impact on itself, not only in the short term but also in the long term. The characteristics for the pork price are different from those for beef and chicken prices. Specifically, in Fig. 4(c), when the frequency is very low, the time-varying power contribution indicates a relatively small value; that is, changes in the pork price do not have an impact on themselves in a low-frequency domain. This implies that the effects of changes in the pork price on itself last for a shorter time than those of changes in the beef and chicken prices on themselves. These differences in characteristics can be clearly seen from Fig. 5(a), (e), and (i).

Fig. 4(b), (c), and (h) display similar characteristics. As an example, we describe the relationship between changes in the chicken price and changes in the beef price. From Fig. 4(c), we cannot confirm an influence of changes in the chicken price on changes in the beef price.

We note that Fig. 4(d), (f), and (g) to Fig. 6(d), (f), and (g) exhibit similar features. For example, from Fig. 4(d)–6(d), we note that changes in the beef price impact on changes in the pork price, to some degree, in the low-frequency domain. This implies that changes in the beef price have had a long-term influence on changes in the pork price.

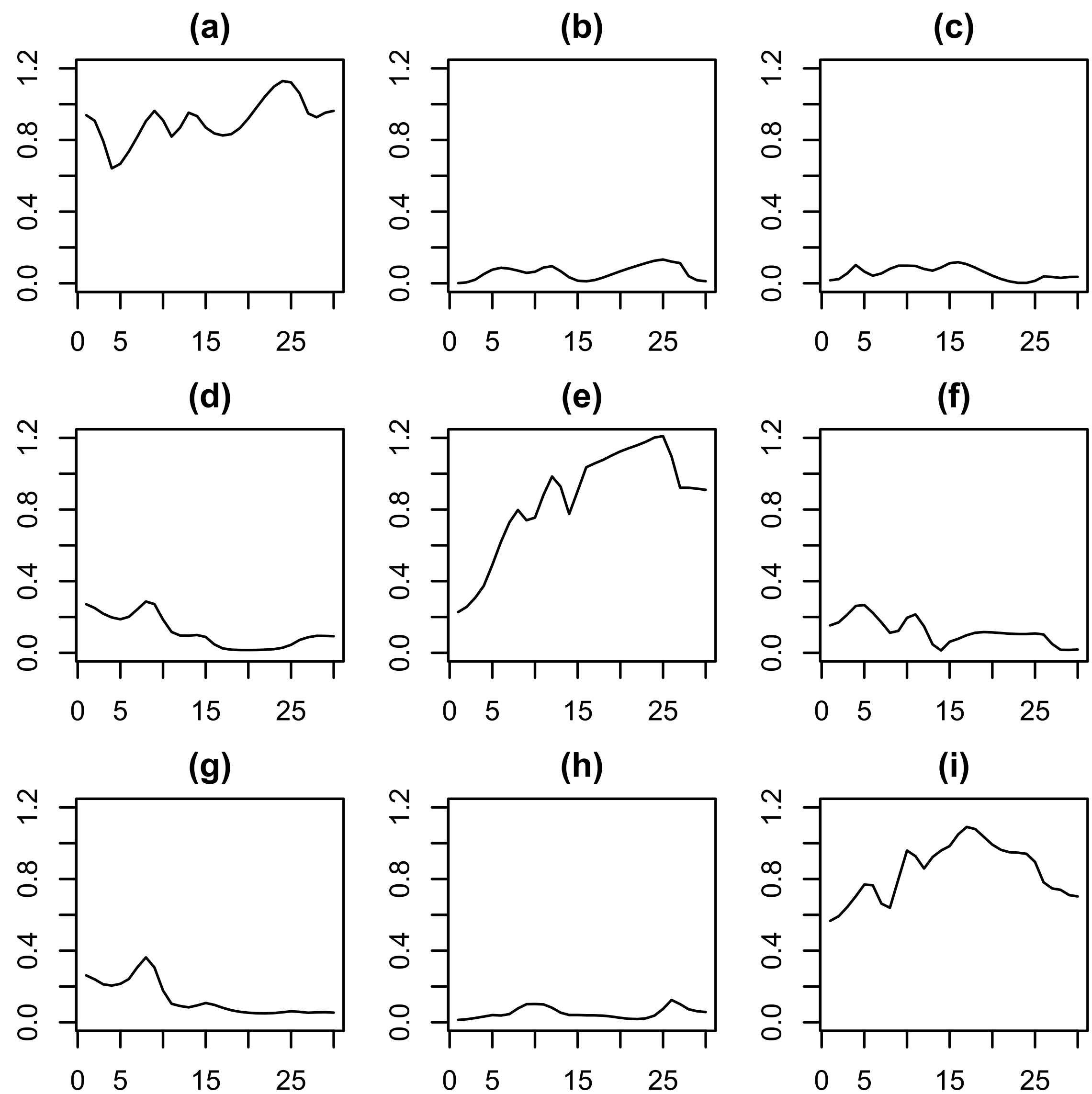

Fig. 5. Relationship between frequency and the power contribution in the time averaging value.

Additionally, from Fig. 4(f)–6(f), changes in the chicken price have had a long-term influence on changes in the pork price. From Fig. 4(g)–6(g), changes in the beef price have had a degree of long-term influence on changes in the chicken price.

Following a comprehensive consideration of Figs. 4–6, we can summarize the key findings as follows: Changes in the beef price have long-term influences on changes in the pork and chicken prices. We observe such influences throughout the period from April 1990 to March 2014, irrespective of the outbreaks of BSE in September 2001 and bird flu in January 2004 in Japan. Additionally, changes in the pork and chicken prices have an effect on changes in the beef price. Moreover, we can find a relationship between changes in the pork price and changes in the chicken price.

We now consider Fig. 7 regarding the estimated TVCV.

Regarding the common range of the vertical axis in Fig. 7, the maximum value is 0.0009 and the minimum value is −0.0003. In Table 3, we summarize the meaning of the nine panels in Fig. 7.

Fig. 7(a) shows that the time-varying self-covariances are relatively large when the lag times are one or two. This implies that there are clear relationships between changes in the beef price in the present and changes in the beef price in the past two months. However, beef price changes in the present have few relationship with beef price changes going back 3 months or more.

Fig. 7(i) shows that the time-varying self-covariances are not large in the period from the 1990s to the mid-2000s. However, since the late 2000s, there has been a growing linkage between changes in the chicken price in the present and changes in the chicken price in the past two months.

Similar characteristics can be observed in Fig. 7(b)–(h). As an illustrative example, when we focus on Fig. 7(b), there is a certain level of correlation between changes in the beef price in the present and changes in the pork price in the past two months. However, we cannot find a definite correlation when lag times are 3 months or more.

To summarize, a close relationship exists between beef price changes in the present and beef price changes in the past two months for the period from April 1990 to March 2014. Moreover, since the late 2000s, changes in the chicken price in the present have had a relationship with changes in the chicken price in the past two months. Price and Gislason [15] estimated demand models for five commodities using annual retail-level Japanese data and found that lags existed for meat and cereal, which shows that habit is important for these commodities. Considering empirical evidence from Price and Gislason [15], the

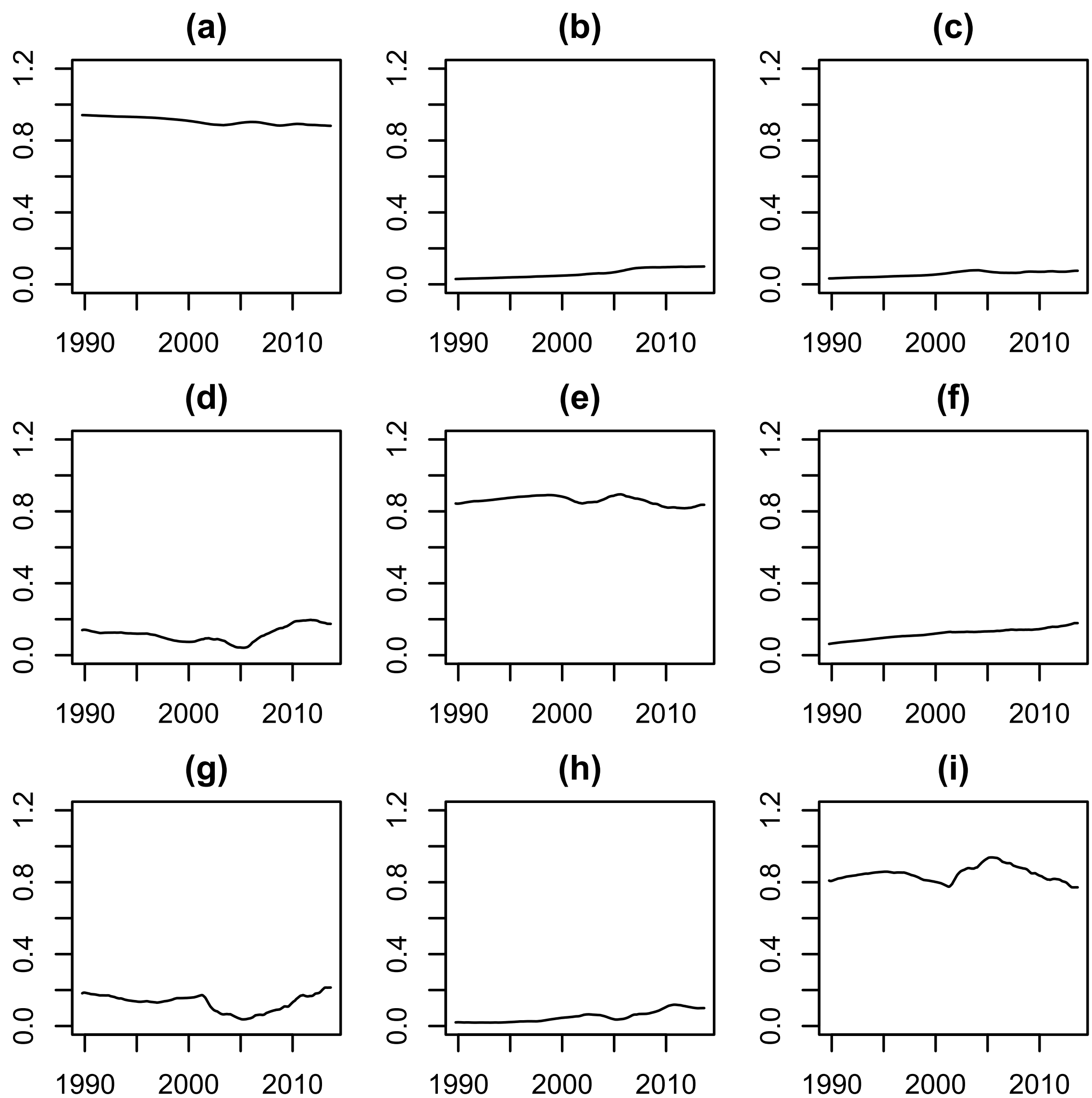

Fig. 6. Relationship between time and the power contribution in the frequency averaging value.

relationships between the beef (chicken) price changes in the present and the beef (chicken) price changes in the past may reflect the habit effect with respect to demand for beef and pork in Japan.

[16] investigated the impact of the BSE and bird flu outbreaks on meat demand in Japan. Their empirical evidence showed that the BSE and bird flu scares caused a fall in demand for beef and chicken, respectively, and an upturn in the demand for pork and seafood. However, our results suggest that changes in the beef price have had less of an influence on changes in the pork and chicken prices. Additionally, changes in the chicken price have had weak effects on changes in the beef and pork prices. Hence, changes in meat prices and changes in meat demand experienced different effects following the BSE and bird flu outbreaks in Japan.

5. Conclusion

Many studies on meat prices have focused on demand-side issues for meat, such as the elasticity of meat demand with respect to meat price (see Refs. [17,18]. However, to the best of our knowledge, there have been few studies in which researchers have attempted to examine the dynamic relationships among meat prices. Therefore, a key contribution of this study is that we presented estimation results for the dynamic relationships among changes in the prices of beef, pork, and chicken in Japan. Additionally, in contrast to related studies, we proposed a TVC-VAR modeling approach to examine interdependences among changes in meat prices, considering time series with non-stationary covariance and structural changes. This is the methodological contribution of this study. Our proposed approach can also be applied to analyzing interdependences among changes in prices of other products, such as vegetables or soft drinks.

The main results are summarized as follows: Changes in the beef price had a long-term influence on changes in the pork and chicken prices during the period from April 1990 to March 2014, irrespective of the BSE and bird flu scares in Japan. However, changes in the pork and chicken prices had only a weak effect on changes in the beef price. Additionally, changes in the beef price in the present are closely related to changes in the beef price in the past two months. Furthermore, since the late 2000s, changes in the chicken price in the present have had a relationship with changes in the chicken price in the past two months.

Based on our empirical analysis, there has been no long-term influence of the BSE outbreak on the dynamic relationships among changes in the prices of beef, pork, and chicken in Japan, although [16] found that

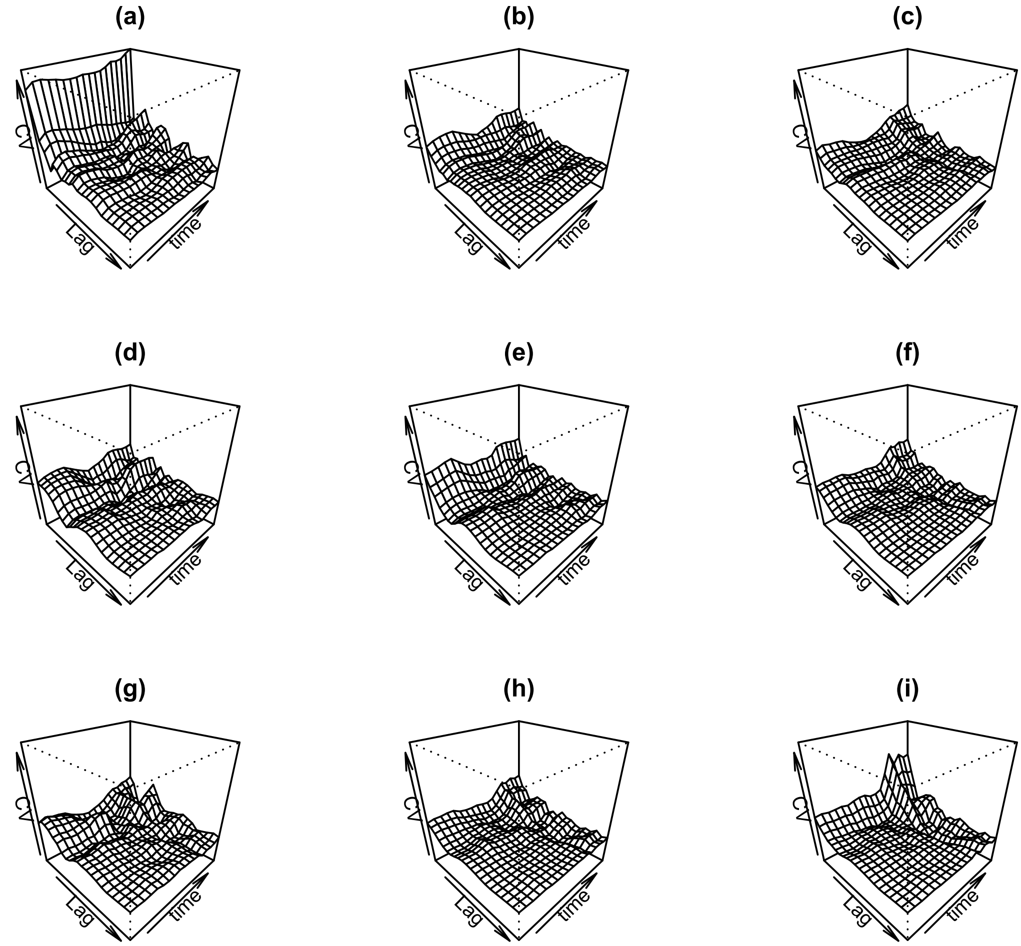

Fig. 7. Time-varying covariance.

Table 3
Time-varying covariance.

panel	meaning	range of TVCV value (min, max)
(a)	TVCV between beef price changes in the past and beef price changes in the present	(−0.0003, 0.0009)
(b)	TVCV between pork price changes in the past and beef price changes in the present	(-8.0213×10^{-5}, 0.0003)
(c)	TVCV between chicken price changes in the past and beef price changes in the present	(-9.4670×10^{-5}, 0.0003)
(d)	TVCV between beef price changes in the past and pork price changes in the present	(−0.0001, 0.0003)
(e)	TVCV between pork price changes in the past and pork price changes in the present	(-1.2002×10^{-4}, 0.0004)
(f)	TVCV between pork price changes in the past and pork price changes in the present	(-9.2144×10^{-5}, 0.0003)
(g)	TVCV between beef price changes in the past and chicken price changes in the present	(−0.0001, 0.0003)
(h)	TVCV between pork price changes in the past and chicken price changes in the present	(-8.5865×10^{-5}, 0.0003)
(i)	TVCV between chicken price changes in the past and chicken price changes in the present	(-1.6314×10^{-4}, 0.0006)

BSE had a persistent influence on consumers' demand for beef, pork, and chicken. Therefore, in Japan, the prices of various meats may adjust more readily over a short period compared with demand for those meats in response to an exogenous shock.

Finally, the direction of future study can be stated as follows: The global impact of COVID-19 that occurred in December 2019 has forced changes in household behavior, which may have caused changes in the structure of the household consumption of meat. Therefore, analysis that includes the most recent data from 2019 onwards would be an interesting future task.

Declaration of competing interest

The authors declare no conflicts of interest associated with this manuscript.

Data availability

Data will be made available on request.

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