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Capturing Changes in Asymmetric Price Transmission : A Rolling Window TAR Estimation Using Bluefin Tuna Case Study

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【abstract】

In this paper, asymmetric price transmission (APT) from producer prices to wholesale prices is estimated with a threshold autoregressive (TAR) rolling window regression model using the data of bluefin tuna in Japan. Rolling window regression is a methodology that repeats regressions using dataset subsamples by shifting the start and end points with a fixed window. Hence, the rolling window regression captures potential time-varying parameters. The findings of this study supported those of Matsui *et al.* (2011). However, the rolling window regression is more robust as a statistical methodology than regressions with total sample. Furthermore, it provides more information on the process of changes in the APT compared to estimations with sample separations based on descriptive analysis or structural change tests. TAR estimations with sample separation can be considered to be a special case of the rolling TAR without overlapping time periods.

【keywords】

rolling window, TAR model, cointegration, asymmetric price transmission

1. Introduction

The threshold autoregressive (TAR) model developed by Enders and Granger (1998) and Enders and Siklos (2001) is a popular econometric model for estimating asymmetric price transmission (APT) with nonstationary time series data. As mentioned in the survey paper by Meyer and von Cramon-Taubadel (2004), price transmission is said to be asymmetric if the speed or the amount of adjustment of the output price differs after the input price increases or decreases. Many empirical studies on various commodities have been conducted using the TAR model. These studies illustrated the existence of APT from the prices of an upstream industry to those of a downstream industry.

Previous empirical APT studies that use the TAR model for agricultural products include that of Abdulai (2002), who analyzed the Swiss pork market; Ghoshray (2002), who estimated the APT for wheat export prices in major wheat-producing countries; Hassan and Simioni (2001), who considered the APT from shipping prices to retail prices in the vegetable market in France; and Nakajima (2010), who analyzed the APT of U.S. corn from the export prices in the U.S. to the import prices in Japan.

For fishery products, Gonzales *et al.* (2003) analyzed the marine products market in France and identified downward rigidity in price transmission from the landing prices for cod to their retail prices and upward rigidity from the import prices for salmon to their retail prices. Jaffry (2004) analyzed the French hake value chain and concluded that retailers responded to positive changes in auction prices more quickly than they did to negative changes. Matsui *et al.* (2011) estimated the momentum-TAR, or M-TAR, model using Japanese bluefin tuna data and showed that the price transmission was asymmetric, in that the consumption market prices adjusted more rapidly when the farm-gate prices increased than when they decreased in the latter half of the 1970s through the end of the 1980s. Then the price transmission changed to another asymmetry in which the consumption market prices adjusted more slowly when the farm-gate prices increased than when they decreased in the 1990s.

There are some problems, however, in these previous studies that employ the TAR model. One problem is that the sample period was selected rather arbitrarily. Because the values of the coefficients in the model are sensitive to the selected sample period, it is necessary for researchers to carefully consider possible changes in the estimation results by changing the sample period. TAR estimations should be conducted based on the sensitivity of different sample sizes.

Another problem, which is closely related to the one mentioned above, is that previous studies rarely focused on possible time-varying parameters in TAR estimations. This problem is a cause for concern, because if structural changes exist and estimated parameters vary in different subsamples, then the estimates may be biased and the estimation results in the total sample may provide misleading conclusions and implications. Some papers mentioned potential structural changes based on descriptive analysis and divided the sample period into subsamples. Then, they estimated the TAR model for each subsample (Enders and Siklos (2001), Matsui *et al.* (2011), etc.). However, this methodology lacks a statistical background of the sample divisions and is unable to completely eliminate the arbitrariness of (sub)sample selection. Other studies employed structural change tests such as the sequential Chow test (Abdulai, 2002) and Bai and Perron's (2003) multiple structural change tests (Nakajima *et al.*, 2010). Nevertheless, there is no adequacy in the rigorous manner of estimating changes in asymmetry using OLS residuals.

The purpose of this study is to illustrate a methodology more robust than that of previous studies for estimation of the APT using the TAR model in a manner. Our methodology captures possible structural changes by estimating possible time-varying parameters in the model. In particular, in this study, rolling window regressions are employed that run sequential regressions by shifting the start and end points of the sample with a constant interval and a fixed subsample (window) size(1).

The rest of this paper is organized as follows. In Section 2, the rolling window methodology and the rolling TAR model are explained. In Section 3, an empirical analysis of the rolling TAR is conducted using bluefin tuna data, same as that employed by Matsui *et al.* (2011). Finally, in Section 4, we provide the conclusions.

2. Methodology and model

2-1. Rolling window regression

As explained in Zivot and Wang (2006), rolling analysis of a time series model is often used to assess the model's stability over time. Although the model's parameters are assumed to be constant over time in the time series analysis, this assumption may not be true, because the economic environment often changes. One of the common techniques for assessing the constancy of a model's parameters is to compute the parameter estimates over a rolling window of a fixed size in the sample. If the parameters are truly constant over the entire sample, then the estimates over the rolling windows should not be very different. However, if the parameters change at some point during the sample, then the rolling estimates should capture this instability.

In general, the rolling window regression is a methodology that repeats regressions using subsamples of total data by shifting the start and end points with a fixed window. Consider an OLS estimation with time series data using the rolling window as follows:

$$y_{t(i)} = a_i + b_i\, x_{t(i)} + e_{t(i)} \quad i = 1, \cdots, n, \tag{1}$$

where y is the dependent variable, x is the vector of independent variables, a and b are parameters, e is the error term, and i is the number of rolling regressions.

Note that both the intercept and the slope parameter may change in each regression i. If the total observation number is N, the window size is set to be w, and the increment interval, or the increment of the time period, between the adjacent rolling regressions is d, then n is written as follows:

$$n = \left\lfloor \frac{N-w}{d} \right\rfloor + 1, \tag{2}$$

where $\lfloor X \rfloor$ stands for the floor of X, that is, the largest integer less than or equal to X. In most cases, the regressions are conducted by increasing the start and end points by 1, that is, $d=1$; hence, $n = N - w + 1$. In addition, $t(i) \in [i, i+w-1]$ for each i.

Using data with a total sample size of 500 and setting a window size of 100, regressions are conducted initially using periods 1–100, followed by periods 2–101, 3–102, ..., and finally periods 401–500. The total number of regression results (the total sample size minus the window size plus one) for each parameter is 401. In this manner, possible time-varying parameters are obtained for a given sample.

The parameters of rolling window regressions depend on the interval of each regression and window size. The larger the interval, the more coarse must be the change in the parameters. It is recommended that smaller intervals, such as one, be chosen by considering the functional processing ability of computers. As for window size, the smaller the window size, the more detailed the movement of the time-varying parameters; however, in this case, the variation in the movement is large (Su and Hwang, 2009). Conversely, a large window makes it difficult to determine possible structural changes in the subsample.

The window size depends on the choices or the aims of the research. Swanson (1998) used 10-year (120-month) and 15-year (180-month) windows, while Su and Hwang (2009) compared the estimation results of 13, 25, 39, and 51 windows. In any case, some sensitivity tests should be conducted during the empirical analysis.

2–2. Rolling window with the TAR model

The rolling TAR model is introduced on the basis of the methodology of the rolling window regression. The TAR model is explained in detail in Enders and Siklos (2001), Nakajima (2010), and Matsui *et al.* (2011). Hence, only the essence of the model and the difference in the rolling windows are shown here.

The first step is to regress the output price (p_{2t}) on the input price (p_{1t}) to obtain the residuals $\{\hat{\mu}_t\}$, which may be serially correlated. If p_{1t} and p_{2t} are nonstationary (I(1)) variables and $\{\hat{\mu}_t\}$ is the stationary (I(0)) variable, then p_{1t} and p_{2t} are said to be cointegrated (Engle and Granger, 1987).

In a rolling TAR model, whether $p_{1t(i)}$ and $p_{2t(i)}$ in the i th regression are cointegrated can be tested using the following equation for each regression i:

$$\Delta\mu_{t(i)} = I_{t(i)}\rho_{1i}\mu_{t(i)-1} + \left(1 - I_{t(i)}\right)\rho_{2i}\mu_{t(i)-1} + \sum_{j=1}^{T_i}\gamma_{ji}\Delta\mu_{t(i)-j} + \varepsilon_{t(i)}, \tag{3}$$

$$I_{t(i)} = \begin{cases} 1 & \text{if} \quad \mu_{t(i)-1} \geq \tau_i \\ 0 & \text{if} \quad \mu_{t(i)-1} < \tau_i \end{cases}, \tag{4}$$

where $I_{t(i)}$ is the Heaviside indicator function; ρ_{1i}, ρ_{2i} (2), and γ_{ji} are parameters; τ_i is the super-consistent estimator of the threshold that minimizes the sum of the squared residuals (RSS) of Equation (3) by using the grid search method developed by Chan (1993); and $\varepsilon_{t(i)}$ is the white noise disturbance term. For $\{\hat{\mu}_{t(i)}\}$ to be stationary, $p_{1t(i)}$ and $p_{2t(i)}$ need to satisfy the conditions $\rho_{1i} < 0$, $\rho_{2i} < 0$, and $(1+\rho_{1i})(1+\rho_{2i}) < 1$ for any value of τ_i (Petrucelli and Woolford, 1984). T_i is the lag order that satisfies these conditions (hereafter referred as the Conditions) and minimizes either the Akaike information criteria (AIC) or the Bayesian information criteria (BIC).

In the rolling TAR model, a cointegration test is performed by testing whether $\rho_{1i} = \rho_{2i} = 0$ in each regression. If the null hypothesis $\rho_{1i} = \rho_{2i} = 0$ is rejected, then $p_{1t(i)}$ and $p_{2t(i)}$ are cointegrated. The F-statistics are called Φ_i statistics(3). The distribution of the Φ_i statistics is different from those of the normal F-statistics. The critical values given the lag order are shown in Enders and Siklos (2001).

If $p_{1t(i)}$ and $p_{2t(i)}$ are confirmed to be cointegrated, then the APT can be tested by testing the null hypothesis $\rho_{1i} = \rho_{2i}$ (4). If $\rho_{1i} = \rho_{2i}$ is rejected and $|\rho_{1i}| < |\rho_{2i}|$, negative discrepancies from the equilibrium error adjust more rapidly than positive discrepancies. This implies that a shock that decreases margins adjusts more rapidly than a shock that increases margins. That is, the price transmission exhibits downward rigidity, which is called positive APT. In contrast, if $\rho_{1i} = \rho_{2i}$ is rejected and $|\rho_{1i}| > |\rho_{2i}|$, then the positive deviations adjust toward the equilibrium error more rapidly than the negative deviations. This implies that a shock that increases the margin adjusts more rapidly than the one that decreases the margin. This results in upward rigidity, which is called negative APT.

Another formulation of the asymmetric adjustment process exists: instead of using $\mu_{t(i)-1}$, $\Delta\mu_{t(i)-1}$ can be used in Equation (4) as follows:

$$I_{t(i)} = \begin{cases} 1 & \text{if} \quad \Delta\mu_{t(i)-1} \geq \tau_i \\ 0 & \text{if} \quad \Delta\mu_{t(i)-1} < \tau_i \end{cases}, \tag{5}$$

Equation (3) with the indicator function of Equation (5) in each regression represents the rolling M-TAR model.

The TAR and M-TAR models correspond to two asymmetric adjustment processes, deepness and steepness (Sichel, 1993); deepness represents a skewed time series and steepness a skewed first-diffenrence series. However, in both models, $|\rho_{1i}| < |\rho_{2i}|$ indicates positive APT and $|\rho_{1i}| > |\rho_{2i}|$ indicates negative APT. In the empirical studies, TAR or M-TAR is selected on the basis of AIC or BIC (Enders and Granger, 1998). Furthermore, according to power tests in previous studies (Enders (2001), Enders and Siklos (2001), etc.), the M-TAR model has greater power in detecting a cointegration relationship than the TAR model.

3. Empirical analysis

3-1. Data

The data used in this study is the same as that used by Matsui *et al.* (2011), because one of the motivations of this study is to check the validity of sample division. Monthly prices of bluefin tuna (frozen) in both producer and wholesale markets from January 1964 to December 2006 were obtained from the “Annual Report of Distribution Statistics on Fisheries Products” of the Ministry of Agricultural, Forestry and Fisheries.

The price data are transformed into natural logarithmic form and used on a nominal basis, as in many empirical studies of the TAR model, although a sensitivity test is conducted using real price data, where the nominal data are deflated by the consumer price index (CPI) of Japan. The CPI was obtained from the International Financial Statistics of the IMF. Furthermore, we checked the seasonal variation of the data. According to seasonal adjustments using the X12-ARIMA method, the data were found to have limited seasonal variations. We conducted the sensitivity test using the seasonally adjusted data.

3-2. Unit root tests

The unit root tests for the stationarity of (logs of) p_{1t} and p_{2t} were conducted using the ADF and KPSS tests(5), whose results are drawn from Matsui *et al.* (2011) and illustrated in Table 1. The ADF tests indicate that although the null hypothesis

Table 1 Unit root test results

Variable	Difference	ADF test		KPSS test
		t-statistic	p-value	LM statistic
Log of producer price	Level	−2.14	0.52	0.319***
	First-differenced	−16.75***	0.00	0.024
Log of wholesale price	Level	−2.51	0.32	0.163**
	First-differenced	−12.52***	0.00	0.035

Notes:
1) The results are the same as those in Matsui *et al.* (2011).
2) The t-statistics of the ADF tests are obtained by regressions with an optimal lag length, which minimizes the BIC. The p-values are calculated by MacKinnon's (1996) procedure.
3) Lagrange multiplier (LM) test statistics are obtained with Andrews's bandwidth using the Bartlett kernel. The asymptotic critical values are based on Kwiatkowski *et al.* (1992).
4) The test equations in both the ADF and KPSS tests include a trend and an intercept.
5) ***, **, and * represent significance at 1%, 5%, and 10% levels, respectively.

that the time series have a unit root was not rejected in the level series, it was rejected in the first-differenced series at the 1% significance level for both prices. In addition, the KPSS tests indicate that the null hypothesis of no unit root was rejected in the level series at least at the 5% level; however, it was not rejected in the first-differenced series for both prices. Therefore, it follows that both p_{1t} and p_{2t} are I(1) series.

3–3. Rolling TAR results

In the rolling window regression of the TAR model, the window sizes of 10 years (120 months) and 1 month interval were chosen. The window of 120 months is neither too long nor too short. In addition, in the next subsection, rolling window regressions using the window sizes of five years (60 months) and 15 years (180 months) are also conducted as sensitivity tests.

Because the total sample size is 516 and the window size is 120, there are 397 TAR model regressions using subsamples. In each regression, the super-consistent τ_i is estimated using Chan's (1993) method. The lag orders that satisfy the Conditions(6) are selected to minimize the BIC of Equation (3). In addition, in each regression, the parameters are stored only when the price series are confirmed to be cointegrated, where Φ_i statistics are greater than the critical values at the 10% significance level(7). Furthermore, the BIC of each regression is stored to compare the value of the TAR model with that of the M-TAR model. Based on the result of the rolling window regression, TAR and M-TAR models are compared in each regression using BICs.

Table 2 Numbers and percentages of (M−) TAR models selected by the BIC

Model	Case A		Case B	
	Number	%	Number	%
TAR	102	27.3	102	27.7
M-TAR	272	72.7	266	72.3
TAR + M-TAR	374	94.2	368	92.7
Number of regressions	397		397	

Notes:
1) "Case A" indicates that if the BIC in one model is missing and is available in the other, then the model having the value is chosen. Meanwhile, in "Case B", if the BIC in one of the models is missing, then neither model is selected.
2) "Number" of the TAR and M-TAR is the number selected by the BIC.
3) "Number" of the "TAR+M-TAR" is the sum of the "Number" in the TAR and the M-TAR.
4) "%" of the TAR or M-TAR is the percentage of the TAR or M-TAR to "TAR+M-TAR."
5) "%" of the "TAR+M-TAR" is the cointegration percentage of the "TAR+M-TAR" to the number of rolling window regressions.

Table 2 illustrates the numbers and ratios of the TAR and M-TAR models selected in terms of the BIC. In each regression, the model whose BIC is smaller than the other is selected. In Case A, if a BIC value in one model is missing, because at least one of the conditions previously mentioned (the cointegration conditions and the Conditions) is not satisfied, while the other has the value, then the model having the value is chosen. In Case B, if the BIC in one of the models is missing, then neither model is selected. In both cases, it is concluded that the M-TAR model outperforms the TAR model in terms of the BIC, which is consistent with the studies previously mentioned. In addition, note that the ratio of "the sum of TAR and M-TAR selected" and "the number of regressions" is larger than 92%, which indicates that most of the regressions satisfy the Conditions and the price series are cointegrated.

Figure 1 illustrates the movements of the estimated $|\rho_{1i}|$ and $|\rho_{2i}|$ in the rolling M-TAR model. The vertical axis indicates the absolute values of the parameters. The horizontal axis indicates the number of regressions (i) in the ascending order. Figure 1 demonstrates that the value of $|\rho_{1i}|$ is greater or smaller than $|\rho_{2i}|$, where i ranges from 1 to approximately 90; clearly, $|\rho_{1i}|<|\rho_{2i}|$ where i ranges from 90 to 185; $|\rho_{1i}|$ is close to $|\rho_{2i}|$ where i ranges from 185 to 265; $|\rho_{1i}|>|\rho_{2i}|$ where i ranges from 265 to 330; and $|\rho_{1i}|$ is close to $|\rho_{2i}|$ where i ranges from 330 to the end (397). However, it is difficult to conclude whether $|\rho_{1i}|$ is statistically greater or smaller than $|\rho_{2i}|$ when the asymmetry changes. Therefore, significance of the asymmetry and the specific time points are then introduced.

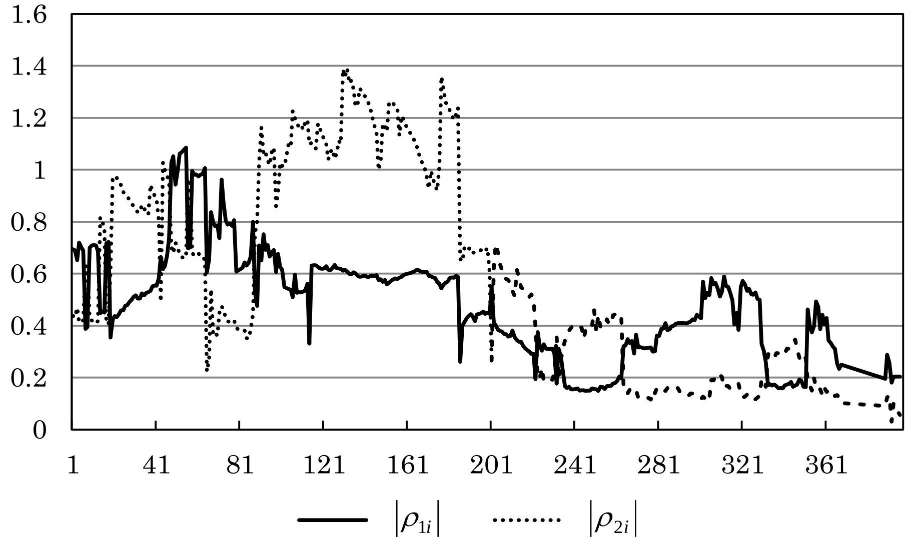


Figure 1 Movements of $|\rho_{1i}|$ and $|\rho_{2i}|$

Notes:
Horizontal axis indicates regression numbers (i).

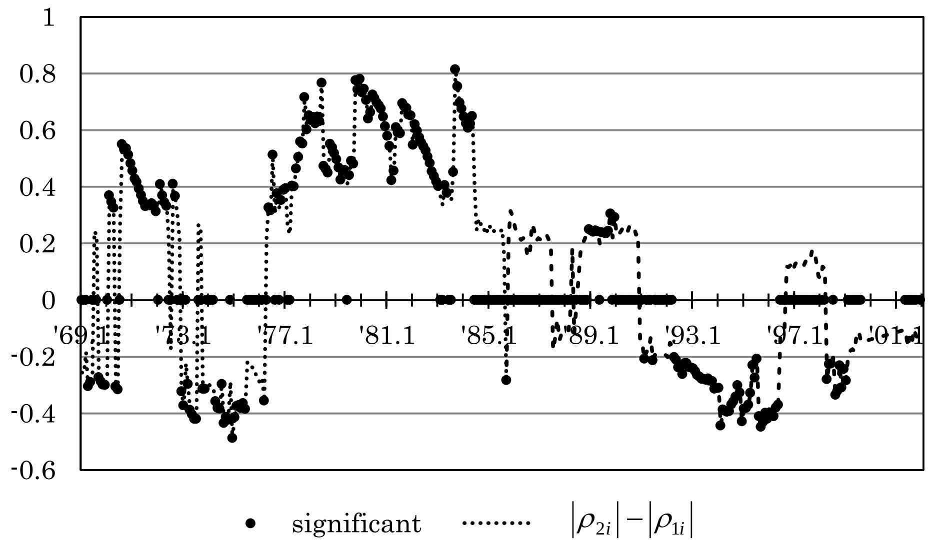


Figure 2 Movements of $|\rho_{2i}|-|\rho_{1i}|$ and significance

Notes:
1) Positive and negative values indicate positive APT and negative APT, respectively.
2) If the null hypothesis $\rho_{1i}=\rho_{2i}$ is rejected at least at the 10% level, bold circles are on the dotted line. If the null is not rejected, the circles are on the horizontal line. The absence of bold circles indicates no cointegration or satisfaction of the Conditions.
3) The median time point of each period of the subsample is chosen as the time point of the regression. It follows that the APT index ranges from January 1969 to January 2002.

The dotted line in Figure 2 shows the value of $|\rho_{2i}|-|\rho_{1i}|$. In addition, the figure shows whether $\rho_{1i}=\rho_{2i}$ is rejected at least at the 10% level. If the null hypothesis is rejected at least at the 10% level, bold circles are located on the dotted line. If the null hypothesis is not rejected, then the circles are located on the horizontal line. The absence of bold circles indicates no cointegration or satisfaction of the Conditions. In addition, the time points are allocated instead of regression numbers; the median time point for each period of the subsample is chosen as the time point of the regression, that is, the time of the i th regression $t=\| [i+(i+w-1)]/2 \| = i + \| (w-1)/2 \|$ (8). For example, the period of the first regression is from January 1964 to December 1973, and the median time point is January 1969. Hence, the result of the regression is assumed to represent the regression result in January 1969(9).

Based on these settings, it cannot be concluded whether $|\rho_{1i}|$ is greater or smaller than $|\rho_{2i}|$ from the end of the 1960s to the end of 1975. However, $|\rho_{1i}|<|\rho_{2i}|$ from 1976 to mid-1984. There is no asymmetry from mid-1980s to early 1992. $|\rho_1|>|\rho_2|$ until mid-1996. No asymmetry was observed from late 1996 to mid-1999. From late 1999 to early 2001, there is no cointegration relationship between the prices. Finally, there is no asymmetry from late 2001 to the end (January 2002).

This result is mostly consistent with that of Matsui *et al.* (2011). In Matsui *et al.* 's study, no asymmetry was observed from 1964 to 1975, positive APT was observed from 1976 to 1989, negative APT was observed in the 1990s, and no cointegration was observed in the 2000s. Although the previous study divided the sample based on a descriptive analysis of the market structure, it did not include a statistical background of the sample separation. In this sense, the result of this study has more objectivity or robustness and more detailed information about the changes in the APT.

3–4. Sensitivity tests

Because the estimation result may change with the characteristics of the data (such as nominal or real and seasonally adjusted or nonadjusted) and the window size, some sensitivity tests were conducted. As shown in Table 3, the ratios of the M-TAR model selected in terms of the BIC are much higher than those of the TAR model in all the estimation results. Hence, the subsequent discussion is based on the results of the M-TAR model.

The results using real data, seasonally adjusted nominal data, and seasonally adjusted real data are shown in Figure 3. Compared to the original result using seasonally nonadjusted nominal data, the one using real data has negligible

Table 3 Percentages of (M−) TAR models selected by the BIC (for the sensitivity test)

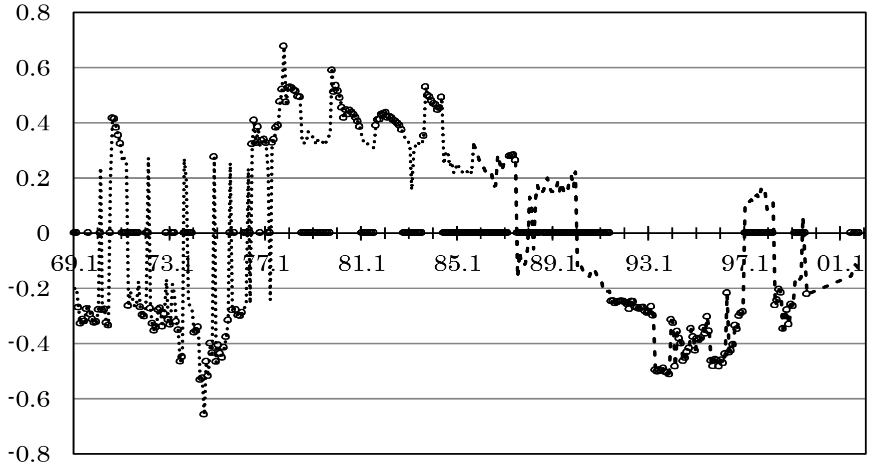
Model	Real		SA		Real+SA		60 window		180 window	
	A	B	A	B	A	B	A	B	A	B
TAR	21.0	21.4	25.2	26.4	24.0	24.4	29.2	29.2	22.6	22.6
M-TAR	79.0	78.6	74.8	73.6	76.0	75.6	70.8	70.8	77.4	77.4
T+M	93.5	91.9	95.0	90.7	91.2	87.7	61.5	53.2	100.0	100.0

Unit: %
Notes:
1) "T+M," "A," and "B" are the same as "TAR+M-TAR," "Case A," and "Case B," respectively, in Table 2. The meaning of each notation is the same as that in Table 2.
2) "Real" is the result using real (deflated) data and "SA" is the result using seasonally adjusted data.

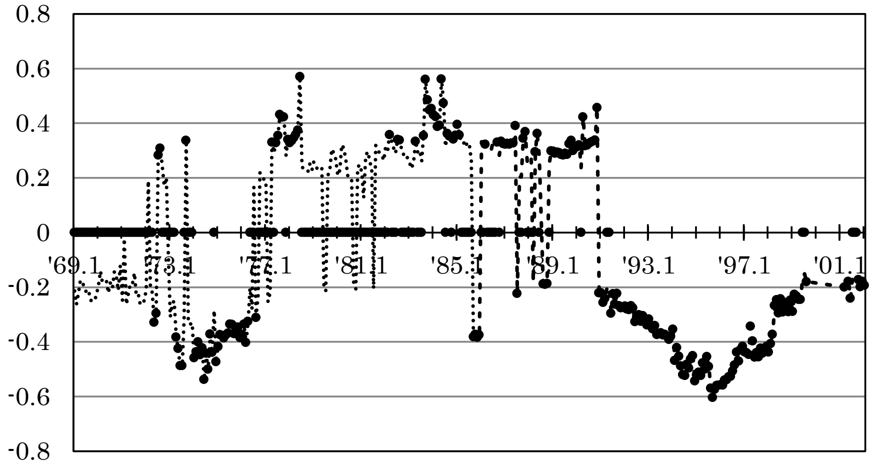
difference. The APT seems to be more negative from the end of the 1960s to mid-1970s. The result using seasonally adjusted nominal data shows less positive APT in earlier periods, more symmetry in the early 1980s, and more positive APT in the late 1980s, compared to the original one. Meanwhile, the result of the seasonally adjusted real data shows less positive APT in earlier periods and more positive APT in the late 1980s, compared to the original one. However, in either case, the movements of the APT are similar to that of the original result, that is, no APT was observed in the earlier period, positive APT was observed from the mid-1970s, negative APT was observed in the 1990s, and no APT was observed in the 2000s.

The results using the window sizes of five years (60 months) and 15 years (180 months) are shown in Figure 4. Note that the time range on the horizontal axis is different from the original result, because the median of the time period in each regression differs according to the window size. The result with the 60 window shows a rather unstable movement of the APT, although the movement is similar to the original one. Because the sample size is small, it is difficult to find the cointegration relationship between the prices, particularly from the late 1990s. This is confirmed in Table 3, where the percentage of the TAR and M-TAR models showing cointegration is much smaller than in the other models (approximately 50% or 60%)(10).

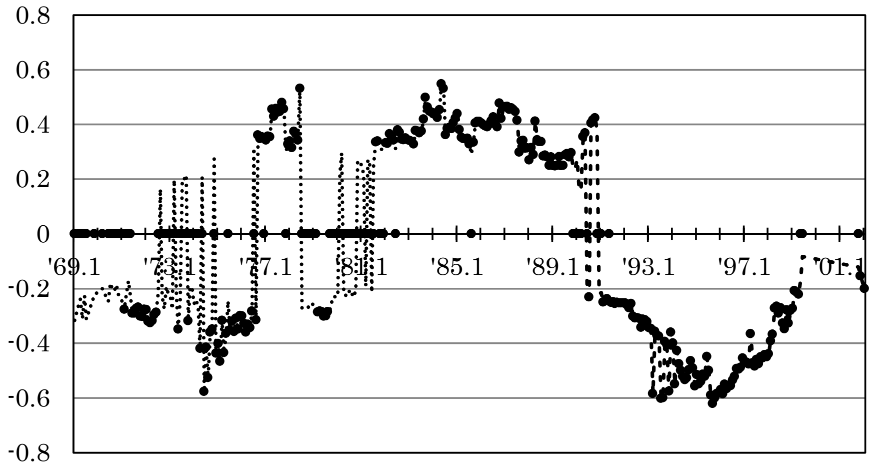
In contrast, the result with the 180 window represents positive APT from the end of the 1970s to mid-1980s and negative APT from the late 1980s to the end of the 1990s. According to Table 3, the prices are cointegrated in all the results. The movement seems rather smooth, that is, there is less fluctuation in the short term. However, this indicates that the regressions are unable to capture possible structural changes and obtain consistent results. Comparison of these results with those of different window sizes reveals that the results with the 120 window fluctuate moderately and capture



(1) Real price data



(2) Seasonally adjusted nominal price data

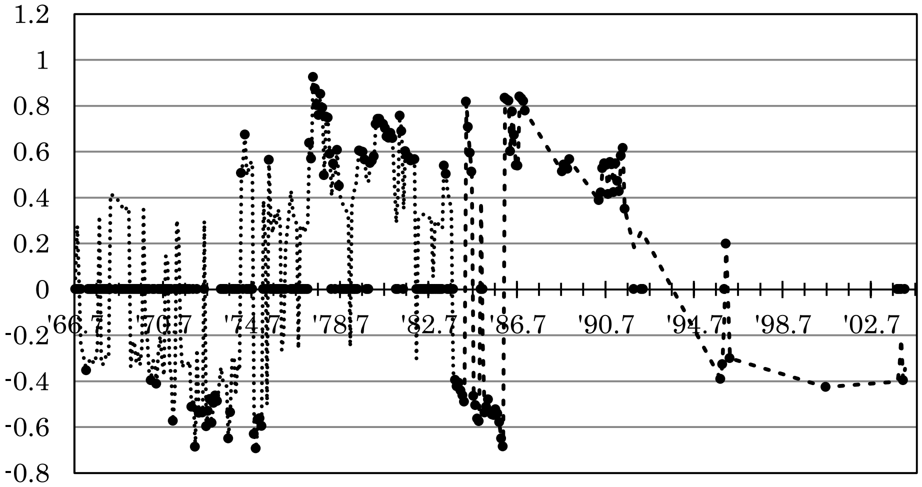


(3) Seasonally adjusted real price data

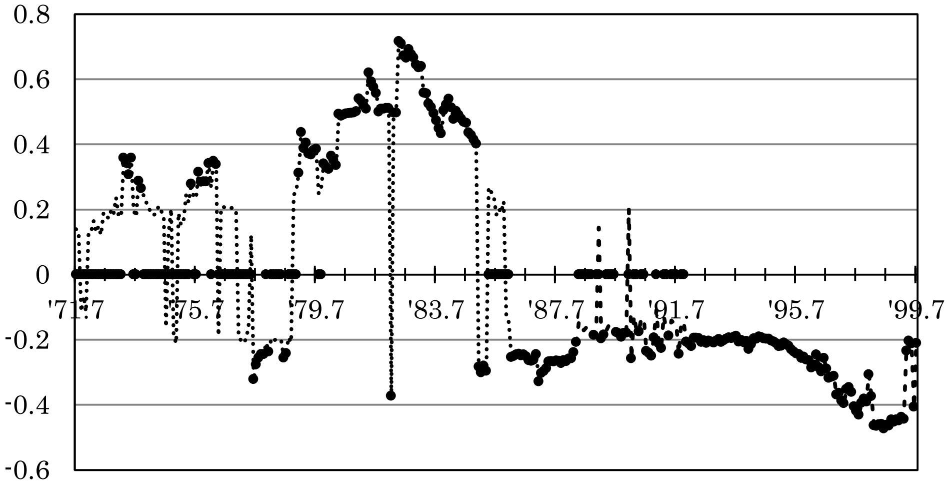
Figure 3 Trend in APT (for real, seasonally adjusted, and seasonally adjusted real data)

Notes:

Notations are the same as those in Figure 2.



(1) 60 window



(2) 180 window

Figure 4 Trend in APT（for the window sizes of 60 and 180）

Notes:

Notations are the same as those in Figure 2, except that the period is from July 1966 to July 2004 for the figure using the 60 window and from July 1971 to July 1999 for the figure using the 180 window.

the movement of the APT rather well. Furthermore, the trend of the APT is similar in each window size, although the timings of the changes differ slightly.

4. Conclusions

In this paper, the APT from producer prices to wholesale prices is estimated with the rolling window regression of the TAR model using Japanese bluefin tuna data. The estimation results indicate positive, negative, or no APT from the 1960s to the end of 1975. Furthermore, APT was positive until mid-1984. The APT gradually changed from positive to negative with the period of no asymmetry from the mid-1980s to early 1992. The negative APT continued until mid-1996, after which there was no asymmetry until January 2002 (the end of the rolling regression). In addition, there was no cointegration relationship between prices from late 1999 to early 2001.

The transition of the APT previously mentioned corresponds to the changes in the market structure of bluefin tuna in Japan. As shown in Matsui *et al.* (2011), the market structure of the sellers became oligopolistic, particularly after the promotion of vessel-based trade, which was prominent in the 1970s. In the 1990s, however, many sellers entered the industry, increasing the number of sellers. Furthermore, the buyers' market power was thought to increase because of the emergence of large retailers such as supermarkets. From the end of the 1990s, a large amount of farmed tuna was imported and traded in Japan, which may have caused another change in the market structure.

According to the sensitivity tests, there is little difference in the trend of the APT, even though the data are transformed from nominal to real, seasonally adjusted nominal, and seasonally adjusted real data. Furthermore, the trend itself does not change according to the window sizes. However, the timing of the changes in the trend differs slightly, particularly when different window sizes are applied.

The empirical results using the rolling window TAR estimation are more convincing than those using the conventional TAR, because the rolling window TAR estimation is more robust since it captures the time variations of the parameters. Furthermore, it includes more information about the changes in the APT, as demonstrated in this study. That is, compared to the findings in Matsui *et al.* (2011), this study seems more convincing from the perspective of the changes in the APT. One reason for this is that the study captured the transition of the APT more concretely, because the movement of the APT was indexed like a set of time series data. In contrast, the sample separation into four subsamples in Matsui *et al.* (2011) was based on the *ex ante* information of the market structure and was not drawn *ex post* by an econometric analysis.

Another advantage of this study compared to Matsui *et al.* (2011) is that the findings of this study contain more information about the changes in the APT. Matsui *et al.* (2011) found that the APT changed from positive in 1976–1989 to negative in the 1990s and concluded that the result "implied" a structural change in the downstream industry, which might affect the structure of the upstream industry. This implication should be a type of conjecture, because the opposite signs of the APT during different time periods do not show any process of structural change. In contrast, this paper revealed that the positive APT gradually changed to no APT and then to negative APT. This "clearly showed" the process by which the structural change in the downstream industry affected the structure of the upstream industry in a detailed manner. Thus, as a statistical methodology, the rolling window regression is not only robust but also includes more information about the process of the changes in the APT, compared to estimations with a sample separation based on descriptive analysis or structural change tests. From the perspective of the latter, the TAR estimation with a sample separation can be considered to be a special case of the rolling TAR without overlapping time periods.

This study applied the rolling window methodology to the TAR model and created an APT index by considering the median time point of each regression as the time point of the subsample. This methodology is applicable, with less data demand, to various analyses on price transmissions such as other fishery products. Moreover, the rolling window methodology itself is useful and manageable when analyzing time-varying parameters of any type of regression.

Further research on indexing the changes, which should be consistent irrespective of window sizes, is necessary. Allocation of precise time points to the indicator is another related issue for future research.

Notes

(1) Bermejo *et al.* (2011) used a recursive estimation with a different type of TAR model in which the window size grows with a fixed start or end point.

(2) According to Engle and Granger (1987), if p_{1t} and p_{2t} are cointegrated, then the OLS regression equation of p_{2t} on p_{1t} can be written as the following error correction model (ECM):

$$\Delta p_{2t} = \rho\left(p_{2,t-1} - \alpha - \beta\, p_{1,t-1}\right) + \sum_{j=1}^{k} \delta_{1j} \Delta p_{2,t-j} + \sum_{j=1}^{k} \delta_{2j} \Delta p_{1,t-j} + v_t$$

where v_t is the white noise disturbance term and k is the lag length (Granger's representation theorem). The term $p_{2,t-1} - \alpha - \beta\, p_{1,t-1}$ is called the error correction term and ρ is known as the adjustment coefficient. Equations (3) and (4) are consistent with the ECM, and ρ_{1i} and ρ_{2i} are the adjustment coefficients in the ECM with the indicator function shown in Equation (4) (Enders and Siklos, 2001).

(3) It is possible to verify whether $\rho_{1i} = \rho_{2i} = 0$ by the Student's t-test instead of the F (Φ)-test. However, from the power tests using Monte Carlo simulations, Enders and Siklos (2001) showed that particularly in the M-TAR model, the power of detecting the cointegration relationship is greater in the F (Φ)-test than in the t-test. Previous empirical studies that used the TAR model also employed the F (Φ)-test, rather than the t-test. Hence, we conducted the F (Φ)-test.

(4) Most empirical studies employed the ECM with an asymmetric adjustment to estimate short-run parameters and simulate the impact of exogenous shocks on endogenous variables by estimating impulse response functions. However, the test for the APT was conducted using the TAR model, not the ECM. Furthermore, we focused on the APT and its changes. Hence, we dedicated our analysis to the rolling TAR regression. Analyses on short-run dynamics and impulse responses should be conducted in future research.

(5) The KPSS test was introduced to complement unit root tests such as the ADF test; that is, by testing both unit root and stationarity hypotheses, it is possible to distinguish series that appear to be stationary, series that appear to have a unit root, and series for which the data (or the tests) are not sufficiently informative to ensure whether they are stationary or integrated (Kwiatkowski *et al.*, 1992).

(6) The maxlag was set to three to reduce the computer's burden. Most lags in the regressions are found to be zero. Hence, the setting should not be a problem.

(7) The critical values for the TAR and M-TAR models were chosen to be 6.35 and 5.76, respectively. These are the highest values among the values with various lag length at the 10% level if the observation number is 100, as in Enders and Siklos (2001). In addition, according to Enders and Siklos (2001), as the observation number increases, the critical values decrease. Thus, if the Φ_i statistics are greater than those values, the prices are definitely cointegrated.

(8) $\|X\|$ denotes the nearest integer to X. In this paper, $\|99/2\| = 50$.

(9) Because one of our major interests is to check when the changes in the APT occur, it is necessary for us to allocate a specific time point to the parameters of each regression. However, previous studies on rolling windows did not attempt to specify the time point for each regression. Although no formal methodology exists to allocate the time point for each regression, the one we employ here is considered to be reasonable. Further research should be conducted on this issue.

(10) These values indicate the percentages that satisfied the Conditions and where the prices were cointegrated. Meanwhile, the percentages that satisfied the Conditions were 99.% for Case A and 93.7% for Case B. It follows that when the 60 window is used, the results have a low percentage of "T+M" primarily because no cointegration relationship exists between the prices.

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