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# Asymmetric Price Transmission of Hardwood Lumber Imported by China after Imposition of the Comprehensive Commercial Logging Ban in All Natural Forests

**Lihua Yang [1], Zhonghua Yin [1,*], Jianbang Gan [2] and Fang Wang [1]**

[1] School of Economics and Management, Beijing Forestry University, Beijing 100083, China; ylh2013164@163.com (L.Y.); wangfang226@bjfu.edu.cn (F.W.)
[2] Department of Ecosystem Science and Management, Texas A&M University, College Station, Texas, TX 77843, USA; j-gan@tamu.edu
* Correspondence: yinzhonghua@bjfu.edu.cn

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**Abstract:** The Comprehensive Commercial Logging Ban in All Natural Forests (CCLB) policy, introduced in April 2015, aims to protect all natural forests in China. It has impacted both China's domestic timber supply and imports. We investigated price transmission in China's hardwood lumber imports resulting from the implementation of this policy. We selected three hardwood lumber species, i.e., Sapelli (*Entandrophragma*), Mandshurica (*Fraxinus*), and Laurel (*Terminalia*), and used their daily prices from 30 April 2015 to 30 November 2017. Threshold co-integration and threshold error correction models are employed for this analysis. We identified a structural breakpoint on 30 November 2016, and consequently partitioned the data series into two parts for the two subperiods separated by the breakpoint. The empirical results indicated that there was asymmetric price transmission (APT) for both subperiods. Adjustment of positive price deviations to the long-term equilibrium levels was slower than that of negative price deviations. In the short term, the price of high-quality lumber evolved independently, whereas the price of lower-quality lumber tended to return to the equilibrium. The APT reflects a redistribution of welfare, benefiting the exporters more than the importers. We find that positive discrepancies in each price pair were inclined to be more persistent in the first subperiod than in the second subperiod. This could attribute to the fact that the degree of CCLB intervention in the former one was higher than in the latter one.

**Keywords:** hardwood lumber; China; asymmetric price transmission; threshold co-integration model; threshold error correction model

## 1. Introduction

China is heavily dependent on timber imports because of its limited forest resources [1,2]. China's timber (logs and lumber) imports reached 97 million $m^3$, valued at US $19.9 billion and accounting for 32% of all timber trade value worldwide in 2014 [3]. A sizable portion of China's timber imports, especially in value, is hardwood imports, which reached approximately 29.8 million $m^3$ (US $10.6 billion) in 2014. The import value of hardwood lumber alone reached US $4.3 billion in that year, accounting for 33% of the total global hardwood lumber trade [3] and making China the world's largest importer of hardwood lumber.

To further protect its natural forests, China enacted the Comprehensive Commercial Logging Ban in Natural Forests (CCLB) on 1 April 2015. As a result, the major state-owned forests in Inner Mongolia, Liaoning, Jilin, and Heilongjiang ceased commercial logging completely. In 2016, all state forests suspended commercial logging activities. On 15 March 2017, the CCLB was implemented in all state, collective, and private natural forests. The effects have been remarkable. The timber harvest from natural forests was 5.27 million $m^3$ in 2015, falling to 1.71 million $m^3$ in 2016, and further to 1.26 million $m^3$ in 2017 [4]. Given the immaturity of forest plantations, most domestic large-diameter hardwood came from natural forests [5–7]. Thus, China's hardwood lumber imports soared by 16.38% (in volume) in 2016 and by another 10.61% in 2017 [3].

The CCLB is likely to trigger the asymmetric price transmission (APT) of imported hardwood lumber as well. APT reflects the inability of the market to respond similarly to positive and negative price disequilibria [8], usually because of policy interventions [9–12]. Faced with a major decline in timber production by natural forests, exporters are apt to believe that any price reduction in hardwood lumber imports would be temporary, and any price increase permanent. Exporters tend to respond slowly to positive price deviations from the long-term equilibrium, but comparatively act quickly to negative price deviations.

APT, a microeconomic concept [10] that has received increasing attention, can be divided into several types. For instance, there are positive and negative APTs. A positive APT indicates that an increase in price is transmitted more rapidly or completely than a decrease, while a negative APT indicates the opposite. APT can also be grouped into vertical and spatial components. The vertical APT refers to price transmission of a single product along the supply chain. The spatial APT indicates that prices are transmitted among congeneric products in the same region of an industrial chain.

APT has received growing attention in the past few decades [13]. In an extensive study of 282 products and product categories, Peltzman found asymmetric price transmission to be the rule rather than the exception [14]. The research objects of APT are mainly agricultural products [15–22]. Vertical APT is evident in the supply chains of many such products, including pork in Switzerland and U.S. [19,21], wild cod in France [11], imported salmon in Germany [20] and rice in Bangladesh [22]. Their conclusions were similar: downstream prices react more rapidly to disequilibria induced by upstream price increases than by upstream price decreases. On the contrary, for farmed salmon in France, the downstream retail price responded more slowly to rises than declines in upstream production prices, because the loss of the unit margin was offset by increased sales [11]. Spatial APT focuses on agriculture markets. Using a threshold co-integration framework, Abdulai demonstrated that local maize markets in Ghana responded more quickly to rising prices than to falling prices in the central markets [23]. Ganneval showed that if the price volatility of four commodities (rapeseed, corn, feed barley, and protein pea) was high in France, any price deviations from the long-term equilibrium were corrected rapidly; forward prices became more relevant as price volatility increased [24]. The study on APT of wheat exported from North America showed that USA enterprises exporting low-quality wheat may reduce prices faster (to maintain market share) than Canadian exporters of high-quality wheat [8,25]. The causes of APT (principally transaction costs and market forces) have also been explored extensively for agricultural products markets in Europe, Asia, and Africa [26–30].

APT is also detected in forest product markets. Vertical APT was evident in the Greek roundwood market; consumer prices adjusted more slowly to increases than to decreases in domestic producer prices [31]. The Korean fiberboard industry exhibited a reverse price adjustment that was vertically asymmetric; wholesale prices reacted more rapidly to rises than to fall in factory prices [32]. Similarly, vertical APT was evident in lumber supply chains for the southern and western USA, where prices were more responsive when price margins increased rather than decreased [33]. Sun showed that, in the USA, spatial price transmission of imported wooden beds (from China and Vietnam) was asymmetric, and that Vietnamese exporters aiming to meet the price of Chinese wooden beds responded faster to a price spread expansion than to a price spread contraction [34].

Although studies exploring asymmetry in agricultural product price adjustments have been extensive, few studies have addressed APT in the context of forest products. In particular, to the best of our knowledge, no report has yet evaluated the spatial APT of forest products after a policy intervention. Hence, we investigate the spatial APT of hardwood lumber imported by China in the era of the CCLB. We focus on three representative hardwood trees: Sapelli (*Entandrophragma*), Mandshurica (*Fraxinus*), and Laurel (*Terminalia*) (For all three species, the Latin names are given in parentheses. The English names used to describe the *Terminalia* differ in the countries of origin. "Laurel" is the name used in the leading exporting country (Myanmar)), because they are major hardwood lumber species imported by China and reflect different wood qualities and prices with similar end-uses. We examine their price dynamics and APT using threshold co-integration models and threshold error correction models (TECMs). We show that APT is evident in the market of China's imported hardwood lumber after implementation of the CCLB. Our findings are informative for both policymakers, importers, and exporters while enriching the literature on forest products markets and trade.

## 2. Materials and Methods

### *2.1. Preliminary Analysis of Data*

Sapelli, Mandshurica, and Laurel are the major hardwood lumber species imported by China. Sapelli is imported primarily from Africa, Mandshurica from Russia, and Laurel from Myanmar, Vietnam, and several African countries [35]. The import values of Mandshurica (US $291 million) and Sapelli (US $52 million) are the second-and fifth-largest among all species of hardwood lumber imported in 2016. Laurel has many subspecies, the trade indices of which are not distinguished in United Nations Comtrade. Given their superior properties, these three species are widely used to produce wooden furniture, floors, doors, and interior decorations, and they are substitutes in consumption. We obtained their price data from the China Timber Price Index Network of China's Development and Reform Commission. The database provides daily price information on most timber trading markets in China. All price data were obtained from the Great Southwest Building Material Market in Sichuan, one of the largest timber markets in China. The daily price series were based on the price for the highest single-deal volume for that day. Freight and transportation costs were not included, and for the study period no tariff was imposed on imported lumber. The market prices of all three species, measured in Chinese *yuan* (CNY)/m$^3$, were hierarchical (Figure 1). The average prices of Sapelli, Mandshurica, and Laurel over the study period were CNY6718 (US $1027)/m$^3$, CNY5691 (US $870)/m$^3$, and CNY4006 (US $612)/m$^3$, respectively, reflecting their quality difference. Sapelli is of higher quality than Mandshurica and Laurel, especially in terms of weathering and crack resistance. Given the price fluctuations, we considered that a structural break might have occurred at the end of 2016. The annual average volatility (calculated using the price data) prior to December 31, 2016 was 28% for Sapelli, 34% for Mandshurica, and 49% for Laurel, thus significantly higher than 7%, 8%, and 15% calculated for 2017 for these three species, respectively. Then, we aimed to identify a structural break in the price series using the breakpoint unit root method [36]. The break date was around 30 November 2016, as also supported by the Chow test (Table 1). Thus, the entire sample period was split into two subperiods: the first one was from 30 April 2015 to 30 November 2016, and the second one ran from 1 December 2016 to 30 November 2017. The break date corresponds to the end of the second implementation phase of the CCLB, which is an inflection point in terms of the decline in timber harvests from China's natural forests. The price fluctuations closely reflected the impact of the CCLB.

**Table 1.** Chow test results.

| | Breakpoint | F-Statistic | Log Likelihood Ratio |
|---|---|---|---|
| From Sapelli to Mandshurica | 11/30/2016 | 1.522 *** | 597.324 *** |
| From Mandshurica to Laurel | 11/30/2016 | 1.651 *** | 633.557 *** |

**Notes**:* Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

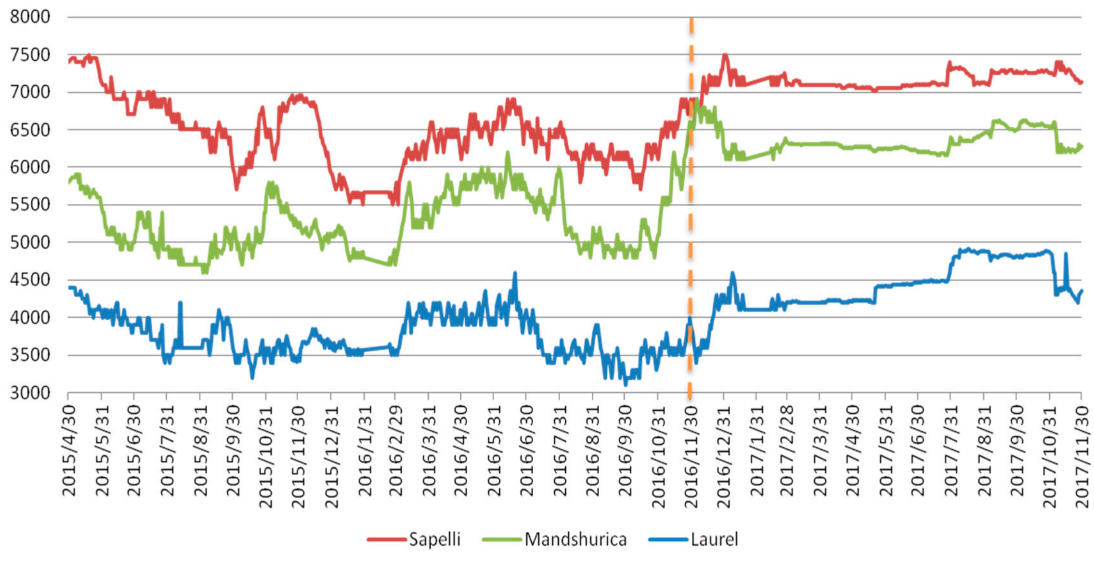


**Figure 1.** The price series of three species of hardwood lumber imported by China between 30 April 2015 and 30 November 2017 (unit: CNY/m³).

### 2.2. Methodology

All price series were converted to natural logarithms to reduce possible heteroscedasticity [24,33]. Two logarithmic price pairs were formed: Sapelli/Mandshurica and Mandshurica/Laurel.

#### 2.2.1. The Linear Co-Integration Model

Linear co-integration has been widely used to explore relationships among price variables. The Johansen and Engle–Granger two-step approaches are the major methods employed. The integration order of price series data is first derived using the Dickey–Fuller GLS (DF-GLS) test or the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test. The null hypothesis of the DF-GLS test is that the variable is nonstationary; the KPSS test assumes that the variable is stationary. If all price series have the same unit roots, Johansen co-integration analysis is appropriate. Johansen (1988), Johansen and Juselius (1990) showed that two-dimensional vector autoregression could be written in the following "error correction" form [37,38]:

$$Z_t = \pi_1 Z_{t-1} + \ldots + \pi_N Z_{t-N} + \varepsilon_t \quad (1)$$

$$\Delta Z_t = \sum_{i=1}^{N-1} \Gamma_i \Delta Z_{t-i} + \Pi Z_{t-N} + \varepsilon_t \quad (2)$$

where $Z_t = (y_t, \ x_t)^T$ is the pair of prices $y_t$ and $x_t$, $N$ is the lag number, and $\varepsilon_t$ is the two-dimensional error vector with a zero mean ($\Delta$ is the variance-covariance matrix). Two quantitative relationships hold among the coefficients ($\Gamma_i$, $\pi_j$, $\Pi$): $\Gamma_i = -I + \sum_{j=1}^{i} \pi_j$ and $\Pi = -I + \sum_{h=1}^{N} \pi_h$, where $I$ is an identity matrix and $i$ is the lag order. The Johansen trace and maximum eigenvalue statistics are used to determine the number of co-integrations between the two price variables. Co-integration of each price pair was tested over both subperiods. The number of lags in each vector autoregressive model (VAR) was determined by reference to the lowest Akaike information criterion and Bayesian information criterion (AIC and BIC, respectively).

Depending on the results of the Johansen test, the Engel–Granger two-step method can be employed to explore the co-integration relationship. The method focuses on the time series properties of residuals under long-term equilibrium [39]. The Engle–Granger two-step formulae are as follows:

$$y_t = \phi_0 + \phi_1 x_t + \xi_t \quad (3)$$

$$\Delta \hat{\xi}_t = \rho \hat{\xi}_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta \hat{\xi}_{t-i} + \mu_t \quad (4)$$

where $\phi_0$, $\phi_1$, $\rho$, $\varphi_i$ are coefficients, $\xi_t$ is the error term, $\hat{\xi}_t$ is the estimated residuals, $\Delta$ is the first difference, $\mu_t$ is a white noise disturbance term, and $P$ is the lag number. The method involves two steps. The first step estimates the long-term relationship of Equation (3) in terms of the price variables. It is essential to define the direction of information flow between long-term equilibrium prices; the Granger causality test may be helpful to this end [24]. We constructed two long-term relationships (Sapelli/Mandshurica and Mandshurica/Laurel). In the second step, the estimated residuals $\hat{\xi}_t$ are used to perform a unit root test [39]. The lag number must be selected to ensure the absence of any serial correlation in the regression residuals $\mu_t$; the Ljung-Box Q test, and the AIC and BIC are helpful. Once the null hypothesis of $\rho = 0$ is rejected, the residual series derived from the long-term equilibrium is deemed to be stationary, thus demonstrating that the two price variables are co-integrated [40].

### 2.2.2. The Threshold Co-Integration Model

The linear co-integration model assumes the symmetry of price transmission to capture symmetric price adjustment. However, to obtain empirical evidence of APT, Enders and Siklos [41] developed a two-step approach for examining threshold co-integration based on the approach of Engle and Granger [39]. It was suggested that the new, nonlinear co-integration model can be used as an alternative method to capture sharp asymmetric movements in a series of estimated residuals. The threshold co-integration model has advantages over other econometric methods for APT, including partial adjustment model [42,43], deterministic regime switching model [44,45], and so on. First, it can apply the standardized cointegrating Dickey–Fuller technique to survey asymmetric adjustment to the long run equilibrium [10]. Second, it can be used to investigate the magnitude and speed of price transmission [31].

Estimation proceeds as follows. First, using the ordinary least-squares method, the long-term equilibrium relationships between price series are derived using Equation (3). Second, the estimated residuals and forming indicators are used to create a threshold autoregression (TAR) model and a momentum threshold autoregression (MTAR) model. The principal equation is Equation (5); Equation (6a,b) yield the indicator variables:

$$\Delta \hat{\xi}_t = \rho_1 H_t \hat{\xi}_{t-1} + \rho_2 (1 - H_t) \hat{\xi}_{t-1} + \sum_{i=1}^{p} \varphi_i \Delta \hat{\xi}_{t-i} + \mu_t \quad (5)$$

$$H_t = 1,\ if\ \hat{\xi}_{t-1} \geq \tau,\ 0\ otherwise; or \quad (6a)$$

$$H_t = 1,\ if\ \Delta \hat{\xi}_{t-1} \geq \tau,\ 0\ otherwise \quad (6b)$$

where $H_t$ represents the Heaviside indicator, $P$ is the lag number, $\rho_1, \rho_2$ and $\varphi_i$ are coefficients, and $\tau$ is the threshold value. The lag $P$ deals with serially correlated residuals, and is selected using the AIC, BIC, or Ljung-Box Q test. Equations (5) and (6a) represent the TAR model ($\tau = 0$), where the indicator variable depends on the previous period residual $\hat{\xi}_{t-1}$. The adjustment is modeled using $\rho_1 \hat{\xi}_{t-1}$ if $\hat{\xi}_{t-1}$ is above the threshold; $\rho_2 \hat{\xi}_{t-1}$ is used if $\hat{\xi}_{t-1}$ is below the threshold. Similarly, Equations (5) and Equations (6b) represent the MTAR model ($\tau = 0$); the previous period change $\Delta\hat{\xi}_{t-1}$ now becomes the key adjustment variable, similar to $\hat{\xi}_{t-1}$ above. In this manner, the TAR captures potential asymmetric deep movements in the residuals; the MTAR model considers steep variations in the residuals. Both methods can be used to capture the potential APT. However, as the MTAR uses the first-order differences of the previous-period estimated residuals as indicator variables, it optimally considers sharper asymmetric price changes [39,41].

If the threshold value is zero, some bias may be introduced. Chan [46] proposed an improved method for threshold selection, which includes three steps as follows. The first step involves placing the possible residuals $\hat{\xi}_{t-1}$ of the TAR model or the $\Delta\hat{\xi}_{t-1}$ values of the MTAR model in ascending order. Next, after excluding 15% of both the largest and smallest values, the best threshold values are determined using the remaining 70% of the values. In the final step, by calculating and comparing the sum-of-squares errors of all potential thresholds, the threshold with the minimum sum serves as a consistent estimate of the threshold value $\tau$. Models with consistent thresholds are termed consistent TAR (CTAR) or consistent MTAR (CMTAR) models, which possess the similar features of the TAR and MTAR models described above.

Given the estimated threshold values, consistent models (CTAR—Equation (6a) with an estimated $\tau$, and CMTAR—Equation (6b) with an estimated $\tau$) were employed to evaluate each price pair. Furthermore, two F-statistics were used to test the features of the two models. The rejection of the null hypothesis (no co-integration) indicates that co-integration relationships exist between the two price series, as revealed by the unique critical values [41]. Another standard F-test was employed to examine the null hypothesis of symmetric adjustment. A negative residual deepness (i.e., $|\rho_1| \leq |\rho_2|$) suggests that increases are likely to persist; decreases tend to revert faster toward the equilibrium. According to Enders and Granger [47], the model with the lowest AIC and BIC will be optimal for further analysis.

The convergence rates of price deviations to the long-term equilibrium in the threshold regression model can be estimated as follows [25]:

$$n = \frac{log(1 - q)}{log(1 - |\rho|)} \tag{7}$$

where $n$ denotes the number of days, $q$ is the proportion of price adjustment, and the absolute value of $\rho$ represents the speed of price adjustment to the equilibrium.

### 2.2.3. Threshold Error Correction Model

To incorporate the effects of asymmetry into the models of price transmission, a TECM was initially developed and then extended by many authors [47–49]. We decompose the error correction terms into positive and negative components to focus on whether positive and negative price differences exert asymmetric effects on short-term dynamic price behaviors. The error correction models are built based on long-term correction of asymmetric relationships, as follows:

$$\Delta x_t = \theta_1 + \delta_1^+ H_t \hat{\xi}_{t-1} + \delta_1^-(1 - H_t)\hat{\xi}_{t-1} + \sum_{j=1}^{J} \alpha_{1j}\Delta y_{t-j} + \sum_{j=1}^{J} \beta_{1j}\Delta x_{t-j} + \vartheta_{1j} \tag{8}$$

$$\Delta y_t = \theta_2 + \delta_2^+ H_t \hat{\xi}_{t-1} + \delta_2^-(1 - H_t)\hat{\xi}_{t-1} + \sum_{j=1}^{J} \alpha_{2j}\Delta y_{t-j} + \sum_{j=1}^{J} \beta_{2j}\Delta x_{t-j} + \vartheta_{2j} \tag{9}$$

where $\delta,\ \alpha,\ \beta\ and\ \theta$ are coefficients and constants, $\vartheta$ is an error correction term, *t* is the time, and *j* is the lag order. The maximum lag *J* is chosen using the AIC statistic and the Ljung-Box Q test; the latter test deals with serial correlation. The error correction term is split into positive and negative components (+ and −); $H_t\hat{\xi}_{t-1}$ and $(1 - H_t)\hat{\xi}_{t-1}$ are both defined using the best-fit model. After estimating short-term asymmetric adjustments by threshold, two *F*-tests are performed: one to explore the weak exogeneity of price variables ($H_{01} : \delta^+ = \delta^- = 0$) and the other to examine asymmetry status ($H_{02} : \delta^+ = \delta^-$).

## 3. Results

### *3.1. Linear Co-Integration Analysis*

The KPSS and DF-GLS indicated that the price series was non-stationary; all prices exhibited a single order of integration in both subperiods (Table 2). When the Johansen approach was used to analyze the first and second subperiods (Table 3), the appropriate lag numbers were 2 and 4, respectively. For both price pairs, the Johansen trace and maximum eigenvalue test results rejected the null hypothesis (no co-integration); both price pairs exhibited single co-integration relationships in both subperiods. As shown in Table 4, in each subperiod, Sapelli was the Granger cause of Mandshurica, and Mandshurica was the Granger cause of Laurel. Thus, Sapelli is the independent variable for the price pair Sapelli/Mandshurica, and Mandshurica is the independent variable for the price pair Mandshurica/Laurel (Equation (3)). The Engle–Granger estimates yielded by Equation (4) are shown in Tables 5 and 6. The null hypothesis of $\rho = 0$ is rejected at the 10% significance level (at least) for each price pair over the entire period. The Engle–Granger approach clearly shows that both price pairs are co-integrated in both subperiods.

**Table 2.** Unit root test results.

| Subperiod 1 | KPSS | DF-GLS | Subperiod 2 | KPSS | DF-GLS |
|---|---|---|---|---|---|
| Level (T,C) | | | Level (T,sC) | | |
| Sapelli | 0.268 *** | −1.542 | Sapelli | 0.187 ** | −2.257 |
| Mandshurica | 0.157 ** | −1.710 | Mandshurica | 0.242 *** | −1.782 |
| Laurel | 0.264 *** | −2.130 | Laurel | 0.168 ** | −2.401 |
| First difference (T,C) | | | First difference (T,C) | | |
| ΔSapelli | 0.149 | −9.311 *** | ΔSapelli | 0.112 | −3.088 ** |
| ΔMandshurica | 0.228 | −8.883 *** | ΔMandshurica | 0.054 | −2.981 ** |
| ΔLaurel | 0.135 | −10.750 *** | ΔLaurel | 0.136 | −3.068 ** |

**Notes**: KPSS, Kwiatkowski–Phillips–Schmidt–Shin; DF-GLS, Dickey–Fuller GLS. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

**Table 3.** Results of Johansen co-integration test of pairwise logarithmic prices.

| | Sapelli/Mandshurica | Mandshurica/Laurel | 5% Critical Value | 10% Critical Value |
|---|---|---|---|---|
| Subperiod 1 | | | | |
| $\lambda_{trace}$ | | | | |
| None | 17.3777 ** | 23.7400 ** | 15.4947 | 13.4288 |
| At most 1 | 5.0404 | 4.7252 | 3.8415 | 2.7055 |
| $\lambda_{max}$ | | | | |
| None | 12.3373 * | 19.0145 ** | 14.2646 | 12.2965 |
| At most 1 | 5.0404 | 4.7252 | 3.8415 | 2.7055 |
| Subperiod 2 | | | | |
| $\lambda_{trace}$ | | | | |
| None | 31.8877 ** | 20.2612 ** | 15.4947 | 13.4288 |
| At most 1 | 5.5698 | 2.6484 | 3.8415 | 2.7055 |
| $\lambda_{max}$ | | | | |
| None | 26.3179 ** | 17.6127 ** | 14.2646 | 12.2965 |
| At most 1 | 5.5698 | 2.6484 | 3.8415 | 2.7055 |

**Notes:** * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

**Table 4.** Causality test results.

| Dependent variable | Chi-Sq. | Prob. | Lag | Dependent Variable | Chi-Sq. | Prob. | Lag |
|---|---|---|---|---|---|---|---|
| Subperiod 1 | | | | Subperiod 2 | | | |
| Sapelli/Mandshurica | | | | Sapelli/Mandshurica | | | |
| Mandshurica | 15.4502 ** | 0.0432 | 8 | Mandshurica | 7.9088 ** | 0.0192 | 2 |
| Sapelli | 11.1817 | 0.1916 | | Sapelli | 11.8903 *** | 0.0026 | |
| Mandshurica/Laurel | | | | Mandshurica/Laurel | | | |
| Laurel | 6.2876 ** | 0.0431 | 2 | Laurel | 17.1264 *** | 0.0043 | 5 |
| Mandshurica | 1.3284 | 0.5147 | | Mandshurica | 20.7198 *** | 0.0009 | |

**Notes**: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

**Table 5.** Results of the Engle–Granger and threshold cointegration model for the first subperiod.

| | Sapelli/Mandshurica | | | Mandshurica/Laurel | | |
|---|---|---|---|---|---|---|
| | **EG** | **CTAR** | **CMTAR** | **EG** | **CTAR** | **CMTAR** |
| lag | 4 | 4 | 4 | 2 | 4 | 4 |
| Threshold | N/A | −0.0295 | −0.0039 | N/A | −0.0760 | −0.0237 |
| $\rho_1$ | −0.0528 ** | −0.0141 | −0.0019 | −0.0883 *** | −0.0468 ** | −0.0347 |
| | (−3.4859) | (−0.7908) | (−0.1129) | (−4.2455) | (−1.7598) | (−1.4892) |
| $\rho_2$ | N/A | −0.0576 *** | −0.0869 *** | N/A | −0.1114 *** | −0.2132 *** |
| | N/A | (−3.0046) | (−4.1320) | N/A | (−3.4368) | (−4.9987) |
| AIC | −4.999 | −4.996 | −5.009 | −4.227 | −4.237 | −4.259 |
| BIC | −4.944 | −4.948 | −4.962 | −4.203 | −4.190 | −4.212 |
| $Q_{LB}$ (1) | 0.886 | 0.938 | 0.978 | 0.722 | 0.873 | 0.839 |
| $Q_{LB}$ (4) | 0.999 | 0.919 | 0.996 | 0.152 | 0.999 | 0.999 |
| $Q_{LB}$ (8) | 0.483 | 0.566 | 0.459 | 0.160 | 0.688 | 0.636 |
| $\Phi$ ($H_0$: $\rho_1 = \rho_2 = 0$) | N/A | 4.729 | 8.537 *** | N/A | 7.032 * | 13.099 *** |
| C.V (5%) | N/A | 7.560 | 6.320 | N/A | 7.560 | 6.320 |
| C.V (1%) | N/A | 10.180 | 8.470 | N/A | 10.180 | 8.470 |
| F ($H_0$: $\rho_1 = \rho_2$) | N/A | 2.886 * | 10.411 *** | N/A | 2.567 | 14.451 *** |
| | | [0.090] | [0.001] | | [0.110] | [0.000] |

**Notes:** EG, Engle–Granger; CTAR, consistent threshold autoregression; CMTAR, consistent momentum threshold autoregression; AIC, Akaike information criterion; BIC, Bayesian information criterion. In terms of the Engle–Granger co-integration model, $\rho_1$ refers to the $\rho$ of Equation (4). The corresponding critical value is −3.087, −3.398, and −4.008 at the 10%, 5%, and 1% level, respectively (Enders, 2010), and the numbers in the parentheses are t-values. $Q_{LB}$ ($p$) denotes the significance level of the Ljung-Box Q statistic, which is used to determine serial correlations based on p autocorrelation coefficients ($p$ = 1, 4, 8). $\Phi$ is the threshold co-integration test using the critical values of Enders and Siklos (2001). F is the standard *F*-test, and the numbers in brackets are *p*-values. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

**Table 6.** Results of the Engle–Granger and threshold co-integration model for the second subperiod.

| | Sapelli/Mandshurica | | | Mandshurica/Laurel | | |
|---|---|---|---|---|---|---|
| | **EG** | **CTAR** | **CMTAR** | **EG** | **CTAR** | **CMTAR** |
| lag | 5 | 5 | 5 | 4 | 5 | 5 |
| Threshold | N/A | 0.0313 | −0.0028 | N/A | −0.0450 | −0.0037 |
| $\rho_1$ | −0.0493 * | −0.0671 *** | −0.0342 ** | −0.0352 * | −0.0083 | −0.0295 *** |
| | (−3.2289) | (−3.1930) | (−1.9600) | (−3.3327) | (−0.5828) | (−2.4364) |
| $\rho_2$ | N/A | −0.0306 | −0.0991 *** | N/A | −0.0789 *** | −0.0812 *** |
| | N/A | (−1.4182) | (−3.1936) | N/A | (−5.1361) | (-3.4502) |
| AIC | −7.157 | −7.156 | −7.172 | −5.675 | −5.730 | −5.737 |
| BIC | −7.089 | −7.077 | −7.092 | −5.607 | −5.650 | −5.657 |
| $Q_{LB}$ (1) | 0.709 | 0.697 | 0.801 | 0.523 | 0.910 | 0.740 |
| $Q_{LB}$ (4) | 0.889 | 0.892 | 0.955 | 0.950 | 0.999 | 0.998 |
| $Q_{LB}$ (8) | 0.453 | 0.487 | 0.502 | 0.693 | 0.758 | 0.675 |
| $\Phi$ ($H_0$: $\rho_1 = \rho_2 = 0$) | N/A | 5.980 | 6.900 ** | N/A | 13.358 *** | 9.325 *** |
| C.V (5%) | N/A | 7.560 | 6.320 | N/A | 7.560 | 6.320 |
| C.V (1%) | N/A | 10.180 | 8.470 | N/A | 10.180 | 8.470 |
| F ($H_0$: $\rho_1 = \rho_2$) | N/A | 1.518 | 3.388 * | N/A | 11.388 *** | 3.672 * |
| | | [0.219] | [0.067] | | [0.001] | [0.056] |

**Notes:** EG, Engle–Granger; CTAR, consistent threshold autoregression; CMTAR, consistent momentum threshold autoregression; AIC, Akaike information criterion; BIC, Bayesian information criterion. In terms of the Engle–Granger co-integration model, $\rho_1$ refers to the $\rho$ of Equation (4). The corresponding critical value is −3.087, −3.398, and −4.008 at the 10%, 5%, and 1% level, respectively (Enders, 2010), and the numbers in the parentheses are *t*-values. $Q_{LB}$ ($p$) denotes the significance level of the Ljung-Box Q statistic, which is used to determine serial correlations based on p autocorrelation coefficients ($p$ = 1, 4, 8). $\Phi$ is the threshold co-integration test using the critical values of Enders and Siklos (2001). F is the standard *F*-test, and the numbers in brackets are *p*-values. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

### 3.2. Threshold Co-Integration Analysis

The threshold co-integrations of the two price pairs in both subperiods, as revealed by the CTAR and CMTAR models, are shown in Tables 5 and 6. All estimated thresholds were near zero; there was no "subjective setting" bias. The Ljung-Box Q tests were used to check the autocorrelation of the residuals $\mu_t$ [41]. The Ljung-Box Q statistics showed that none of the models had the problem of serial correlation at least in a lag of 8. AIC and BIC were common criteria for model selection. After initial imposition of a maximum lag of 8, the AIC and BIC statistics revealed that lags of 4 and 5 in the first and second subperiods (respectively) are sufficient. Given the AIC and BIC statistics, the CMTAR model was selected as optimal to reveal the asymmetry of steep price movements irrespective of price pair and subperiod. The following analysis is based on this model. The point estimates of the $\rho_s$ have signs indicating convergence in the first subperiod (Table 5). The $\rho_1$ values are not significant for either price pair, but the $\rho_2$ values differ significantly from zero at the 1% level. Thus, positive discrepancies converged slowly toward the long-term equilibrium; negative discrepancies exhibited relatively rapid convergence. The estimated *Φ*-statistics are 8.537 (Sapelli/Mandshurica) and 13.099 (Mandshurica/Laurel); the null hypothesis (no co-integration of either price pair) can thus be rejected at the 1% significance level. Furthermore, the estimated *F*-statistics are 10.411 (Sapelli/Mandshurica) and 14.451 (Mandshurica/Laurel), allowing for the rejection of the null hypothesis (symmetric adjustment of both price pairs) at the 1% significance level. The price transmission process is asymmetric in the first subperiod for both price pairs. In the second subperiod, all point estimates of $\rho_1$ and $\rho_2$ are negative, and lie remotely from the zero (Table 6). $|\rho_1|$ is much smaller than $|\rho_2|$ for each price pair. Thus, the convergence speed of a positive deviation from the long-term equilibrium is significantly slower than that of a negative deviation. The null hypothesis (no co-integration) is rejected by the *Φ*-statistics (6.900 for the Sapelli/Mandshurica price pair and 9.325 for the Mandshurica/Laurel price pair); both exceed the critical value at the 5% significance level. The null hypothesis (F-test symmetry) is rejected at the 10% level for each price pair. Therefore, price adjustment asymmetry was evident for both price pairs in the second subperiod. For the Sapelli/Mandshurica price pair in the first subperiod, only the point estimates of negative deviations were significant, with a statistic of −0.0869. Thus, negative deviation ($\Delta\hat{\xi}_{t-1}<$ −0.0039) from the long-term equilibrium, caused by an increase in the price of Sapelli or a decline in the price of Mandshurica, could disappear at a rate of 8.69% per day. If the proportion of a disequilibrium to be corrected is taken to be 90%, then, for $|\rho_2|$ = 0.0869, the number of days taken to correct 90% of the disequilibrium will be: $n = \dfrac{log(0.1)}{log(0.9131)} \approx 25$. It thus requires less than a month to eliminate 90% of the negative disequilibrium. Similarly, for the Mandshurica/Laurel price pair in the first subperiod, about one-third of a month is needed to correct 90% of the negative change. In the second subperiod, for the Sapelli/Mandshurica price pair, the point estimates of positive and negative deviation are significant at −0.0342 and −0.0991, respectively. Thus, the positive deviation ($\Delta\hat{\xi}_{t-1}\geq$ −0.0028) from the long-term equilibrium, caused by a fall in the Sapelli price or rise in the Mandshurica price, could disappear at a rate of 3.42% per day. Similarly, the negative deviation ($\Delta\hat{\xi}_{t-1}$ < −0.0028) could disappear at a rate of 9.91% per day. It would thus require over two months to eliminate 90% of the positive discrepancy, but approximately two-thirds of a month to correct 90% of the negative discrepancy. For the Mandshurica/Laurel price pair in the second subperiod, disappearance of 90% of the positive disequilibrium would require more than 2.5 months; the negative disequilibrium would be corrected in less than one month.

### 3.3. Threshold Error Correction Analysis

In terms of short-term APT, the estimated TECMs given by Equations (8) and (9) are shown in Tables 7 and 8, respectively. The Ljung-Box Q tests rejected the autocorrelation of the residuals $\mu_t$ at least in a lag of 8, and the AIC and BIC statistics indicated that a lag of 5 for each model was appropriate. The weak exogeneity indicated that the null hypothesis ($\delta^+ = \delta^- = 0$) cannot be rejected in terms of the price of the higher-quality lumber of each price pair, except for Sapelli of the Sapelli/Mandshurica pair in the second subperiod at the significance level of 1%. However, the coefficient $\delta^+$ in the Sapelli equation for Sapelli/Mandshurica is significantly larger than zero, and $\delta^-$ is essentially zero. Thus, the prices of the higher-quality lumber of each price pair evolve independently. By comparison, the weak exogeneity tests reject the null hypothesis for the lower-quality lumber of each price pair at the 5% significance level (at least). Thus, the prices of both lower-quality lumbers tend to counter the price disequilibrium. The F-statistics of the null hypothesis $\delta^+ = \delta^-$ verify that Mandshurica of the Sapelli/Mandshurica price pair and Laurel of the Mandshurica/Laurel price pair exhibit short-term APT. In the first subperiod, for the Sapelli/Mandshurica price pair, the coefficients of the threshold error correction terms in the Sapelli equation ($\delta^+$ and $\delta^-$) are not significant, implying that the price of Sapelli may have evolved independently from that of Mandshurica in the short term (Table 7). Only the coefficient of the negative error correction term of the Mandshurica equation ($\delta^-$) is significant, being −0.0729, suggesting that 7.29% of the negative price differential can be eliminated in one day, whereas the Mandshurica price does not respond to any positive price differential. A similar result is obtained for the Mandshurica/Laurel price pair. The price of Mandshurica may fluctuate independently; the negative price differential of Laurel can be adjusted by 24.01% per day, but little adjustment of the positive price differential is evident. In the second subperiod, for the price pair Sapelli/Mandshurica, Sapelli exhibited relatively autonomous price variation. Mandshurica does not react to positive deviation; the negative deviation in Mandshurica price can disappear at a rate of 8.96% per day (Table 8). Similarly, the price change of Mandshurica is undisturbed by that of Laurel in the Mandshurica/Laurel price pair. However, the Laurel equation shows that the daily adjustment speed (7.99%) of a negative change from the equilibrium is more than twice that of a positive change (2.99%).

**Table 7.** Results of the threshold error correction model for the first subperiod.

| | **Sapelli/Mandshurica** | | | | **Mandshurica/Laurel** | | | |
|---|---|---|---|---|---|---|---|---|
| | **ΔSapelli** | | **ΔMandshurica** | | **ΔMandshurica** | | **ΔLaurel** | |
| | **Estimate** | **T-Ratio** | **Estimate** | **T-Ratio** | **Estimate** | **T-Ratio** | **Estimate** | **T-Ratio** |
| $\delta^+$ | 0.0180 | 1.3570 | 0.0101 | 0.6123 | −0.0007 | −0.0456 | −0.0386 | −1.6225 |
| $\delta^-$ | 0.0164 | 0.9767 | −0.0729 *** | −3.5081 | −0.0265 | −0.8877 | −0.2401 *** | −5.3421 |
| $\alpha_1$ | −0.0277 | −0.7850 | −0.1215 *** | −2.7788 | 0.0260 | 0.8455 | −0.2082 *** | −4.4948 |
| $\alpha_2$ | 0.0110 | 0.3069 | 0.0208 | 0.4684 | −0.0072 | −0.2318 | −0.1639 *** | −3.5078 |
| $\alpha_3$ | 0.0135 | 0.3783 | −0.0089 | −0.2015 | −0.0029 | −0.0925 | −0.1297 *** | −2.7938 |
| $\alpha_4$ | 0.0203 | 0.5726 | 0.0512 | 1.1661 | −0.0280 | −0.9247 | −0.0773 * | −1.6960 |
| $\alpha_5$ | 0.0628* | 1.7903 | −0.0869* | −2.0010 | −0.0634 ** | −2.1843 | 0.0191 | 0.4365 |
| $\beta_1$ | −0.1744 *** | −4.0274 | −0.0239 | −0.4452 | −0.1569 *** | −3.4719 | 0.0168 | 0.2465 |
| $\beta_2$ | −0.0864 ** | −1.9674 | 0.0813 | 1.4943 | 0.0312 | 0.6940 | 0.0899 | 1.3278 |
| $\beta_3$ | −0.0399 | −0.9025 | −0.0385 | −0.7022 | −0.0183 | −0.4078 | 0.0599 | 0.8857 |
| $\beta_4$ | −0.0422 | −0.9560 | −0.0261 | −0.4773 | 0.0467 | 1.0408 | 0.0193 | 0.2861 |
| $\beta_5$ | −0.0079 | −0.1810 | −0.0197 | −0.3657 | −0.0851 * | −1.9289 | −0.0593 | −0.8932 |
| AIC | −5.477 | | −5.049 | | −5.032 | | −4.214 | |
| BIC | −5.382 | | -4.955 | | −4.938 | | −4.120 | |
| $Q_{LB}$ (1) | 0.985 | | 0.961 | | 0.976 | | 0.939 | |
| $Q_{LB}$ (4) | 0.999 | | 0.999 | | 0.999 | | 0.997 | |
| $Q_{LB}$ (8) | 0.996 | | 0.987 | | 0.953 | | 0.967 | |
| F ($H_0$: $\delta^+ = \delta^- = 0$) | 1.333 | [0.265] | 6.469 ** | [0.017] | 0.395 | [0.674] | 14.923 *** | [0.000] |
| F ($H_0$: $\delta^+ = \delta^-$) | 0.006 | [0.938] | 10.323 *** | [0.001] | 0.629 | [0.428] | 16.956 *** | [0.000] |

**Notes:** AIC, Akaike information criterion; BIC, Bayesian information criterion. $Q_{LB}$ (*p*) denotes the significance level of the Ljung-Box Q statistic, which is used to determine serial correlations based on p autocorrelation coefficients (*p* = 1, 4, 8). F is the standard *F*-test, and the numbers in brackets are *p*-values. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

**Table 8.** Results of the threshold error correction model for the second subperiod.

| | **Sapelli/Mandshurica** | | | | **Mandshurica/Laurel** | | | |
|---|---|---|---|---|---|---|---|---|
| | **ΔSapelli** | | **ΔMandshurica** | | **ΔMandshurica** | | **Δlaurel** | |
| | **Estimate** | **T-Ratio** | **Estimate** | **T-Ratio** | **Estimate** | **T-Ratio** | **Estimate** | **T-Ratio** |
| $\delta^{+}$ | 0.0518 *** | 3.2707 | −0.0201 | −1.1532 | 0.0074 | 1.2335 | −0.0299 *** | −2.5213 |
| $\delta^{-}$ | 0.0014 | 0.0482 | −0.0896 *** | −2.7819 | 0.0152 | 1.3188 | −0.0799 *** | −3.4742 |
| $\alpha_1$ | −0.1748 *** | −3.4704 | −0.2091 *** | −3.7699 | 0.0370 | 1.312 | −0.1855 *** | −3.3082 |
| $\alpha_2$ | −0.1028 ** | −2.1329 | 0.0141 | 0.2653 | −0.0245 | −0.923 | −0.0505 | −0.9548 |
| $\alpha_3$ | −0.0688 | −1.4517 | 0.0399 | 0.7633 | 0.0094 | 0.3536 | −0.0597 | −1.1334 |
| $\alpha_4$ | −0.0966 ** | −2.0649 | −0.3134 *** | −6.0803 | 0.1044 *** | 3.9733 | 0.1041 ** | 1.9927 |
| $\alpha_5$ | 0.0135 | 0.2774 | 0.1105 ** | 2.0543 | −0.0029 | −0.1088 | −0.0291 | −0.5507 |
| $\beta_1$ | −0.1828 *** | −3.2024 | −0.1066 * | −1.6951 | −0.2859 *** | −5.2339 | 0.3977 *** | 3.6602 |
| $\beta_2$ | 0.0281 | 0.4936 | 0.0798 | 1.2709 | 0.0854 | 1.6569 | 0.1628 | 1.5879 |
| $\beta_3$ | −0.1965 *** | −3.533 | −0.3007 *** | −4.9100 | −0.0586 | −1.1384 | −0.0922 | −0.9007 |
| $\beta_4$ | −0.1387 ** | −2.3683 | 0.0310 | 0.4807 | −0.2945 *** | −5.801 | −0.2254 ** | −2.2323 |
| $\beta_5$ | −0.0986 * | −1.7623 | −0.0554 | −0.8983 | 0.0599 | 1.1533 | 0.0988 | 0.9564 |
| AIC | −7.377 | | −7.184 | | −7.114 | | −5.739 | |
| BIC | −7.240 | | −7.047 | | −6.978 | | −5.603 | |
| $Q_{LB}$ (1) | 0.596 | | 0.977 | | 0.647 | | 0.627 | |
| $Q_{LB}$ (4) | 0.958 | | 0.897 | | 0.782 | | 0.984 | |
| $Q_{LB}$ (8) | 0.519 | | 0.441 | | 0.449 | | 0.986 | |
| F ($H_0$: $\delta^{+} = \delta^{-} = 0$) | 5.349 *** | [0.005] | 4.492 ** | [0.012] | 1.707 | [0.183] | 9.625 *** | [0.000] |
| F ($H_0$: $\delta^{+} = \delta^{-}$) | 2.320 | [0.129] | 3.642 * | [0.057] | 0.355 | [0.552] | 3.601 * | [0.059] |

**Notes:** AIC, Akaike information criterion; BIC, Bayesian information criterion. $Q_{LB}$ ($p$) denotes the significance level of the Ljung-Box Q statistic, which is used to determine serial correlations based on p autocorrelation coefficients ($p$ = 1, 4, 8). F is the standard *F*-test, and the numbers in brackets are *p*-values. * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level.

## 4. Discussion

Our empirical results show that APT is evident in China's market of imported hardwood lumber in the whole period. Whether in the first or second subperiod, the price series present positive asymmetric price transmission in the long and short term. This is, the negative price differential is adjusted by a faster convergence speed than the positive one. This is consistent with the conclusions from the majority of previous studies on spatial APT [13,34]. APT reflects a redistribution of welfare compared to the symmetrical situation, modifying the timing and/or magnitude of changes associated with price adjustments [10]. Hardwood lumber exporters respond more rapidly to negative price deviations than to positive price deviations in the Chinese market. These exporters can better take advantage of the price increases that are unavailable under symmetrical conditions; on the other hand, the hardwood lumber importers seem less responsive or lacking the ability to respond to the price reductions created by APT.

In both the long-and short-term, we find that positive differential in each price pair converges slowly in the first subperiod, while relatively fast in the second subperiod. This indicates that the hardwood lumber exporters are likely to benefit more from an increase of price in the former subperiod than in the latter. The main reason could be that the degrees of the CCLB policy intervention between both subperiods are different. Harvesting from natural forests in China fell sharply over the first subperiod, but less so in the second subperiod. The amount of logging from natural forests in China decreased by 3.56 million $m^3$ from 2015 to 2016, while only dropped by 0.45 million $m^3$ from 2016 to 2017 [4]. Exporters' expectations of price rises would thus be stronger in the first subperiod than in the second one. Thus, positive price discrepancies tended to be more persistent in the former subperiod than in the latter.

## 5. Conclusions

We disclose that APT was evident in Chinese imported hardwood lumber market when the CCLB was implemented. By examining the Shapelli/Mandshurica and Mandshurica/Laurel price pairs, we detect a structural break at the end of the second CCLB phase, which prompts us to divide the study period into two subperiods. The break reflects the different degree of impact of different

CCLB implementation phases. The CMTAR model best-fitted the price series of both subperiods, suggesting that price adjustment may be steep when asymmetry is present. The empirical results from both subperiods show that the import prices of both hardwood lumber pairs were co-integrated in a long-term relationship, and that both short-and long-term asymmetric price adjustments were evident. In the long term, the convergence rates of positive price discrepancies to the equilibrium were slower than those of negative price discrepancies. In the short term, for each pair, the price of higher-quality lumber was minimally affected by the price of lower-quality lumber, but the price of the latter type of lumber tends to follow the price of the former type. Positively asymmetric spatial price transmission in the imported hardwood lumber market of China was uncovered; interactions among price pairs were evident after the forest conservation policy was introduced.

The APT identified herein emphasizes that the hardwood lumber market is inefficient. More effective trade policies would be helpful in the CCLB era to correct for the asymmetries. It may be an effective way for China to reduce import dependence on a few countries by diversifying import sources of hardwood lumber. Furthermore, it is suggested that timber import channels should be unified by industry associations. This aims at increasing the bargaining power of China's importers in trade negotiations. However, APT allows both importers and, to a lesser extent, foreign suppliers to strategize with respect to their responses to future price fluctuations. Various threshold co-integration models can be used to examine the markets for logs, pulpwood, and other major forest products. Such efforts would improve knowledge on the price transmission characteristics of forest products, especially in the international context.

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