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An Assessment of Stumpage Price and the Price Index of Chinese Fir Timber Forests in Southern China Using a Hedonic Price Model

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Abstract: *Research Highlights*: Stumpage price is the most important factor affecting the value of forests. Therefore, an understanding of the factors affecting stumpage prices and trends is critical for effective forest management. *Background and Objectives*: Chinese fir is the most important fast-growing timber species in China, it is also the tree species with the largest trading volume in the stumpage markets of Southern China. The aim of this study was to analyze the determinants and trends of stumpage prices for Chinese fir timber forests. *Materials and Methods*: Data on 928 sales of Chinese fir timber forests transacted between 2007 and 2016 were gathered from the stumpage markets in Southern China. We analyzed the relationship between stumpage prices and sales characteristics using the hedonic price method (HPM) and measured the stumpage price index with a dummy time hedonic index. *Results*: (1) The double logarithmic form of the HPM yielded a more accurate estimate than the semi logarithmic form. The R^2_{ad} values in the nine annual prediction models were all above 80%. Stock volume made the greatest contribution to stumpage price, followed by stand age. Stand area had no significant impact on the stumpage price. (2) Stumpage prices of Chinese fir timber forests fluctuated greatly, especially in 2010 and 2015 when the sequential price indexes were 180.01% and 74.95%, respectively. Taking 2007 as the baseline, we calculated the base price index in 2016 to be 197%, with an average annual growth rate of 7.82%. (3) The stumpage market was associated with a higher degree of risk than the timber market. *Conclusions*: Our findings provide valuable inputs that can guide and facilitate the Chinese government's efforts to optimize resource allocation and standardize the stumpage market.

Keywords: stumpage price; Chinese fir timber forests; hedonic price method; dummy time hedonic index; Southern China

1. Introduction

The prices of stumpage (standing timber) are often considered to be residual, referring to the value that remains after adjusting for profits and deducting all costs from the value of the lumber at the mill [1]. Stumpage prices critically influence the value of forest assets and are consequently a crucial factor determining a forest owner's decision to sell a forest. Therefore, it is pertinent to model and forecast stumpage prices. Previous studies that examined actual stumpage prices paid in individual sales have mainly focused on two aspects: the time series of stumpage prices [2–9] and the factors influencing stumpage prices [10–18]. The former set of studies were aimed at examining the dynamics of stumpage markets, whereas the latter group sought to investigate the relationship between stumpage prices and factors such as harvestable volume density, the total area involved in the sale, and the diameter of the trees. A well-regulated and active market for stumpage and the availability of complete datasets are necessary prerequisites for analyses of stumpage prices. Consequently, such studies have been conducted mostly in developed countries (e.g., the United States, United Kingdom, and Canada), with a limited number of studies conducted in developing and less developed countries. The main purpose of this study was to ascertain the determinants of stumpage prices in China's forestry exchange market. The reform of China's collective forest rights system at the beginning of the twenty-first century [19,20] was based on the premise that the nature of the ownership of collective forest land and the use of forest land would remain unchanged, but the right to use forest land and the ownership of trees would be allocated to individual forest farmers. The Chinese government has encouraged the trade of forest rights to optimize the allocation of forest resources. To encourage further transactions of forest rights, provincial, or regional forestry exchange markets have been rapidly established. Ongoing improvements of these markets and the promotion of forest-based reforms have led to the expansion of the trade in forestry exchange markets. However, studies on the determinants of stumpage prices within China's forestry exchange markets remain limited.

The hedonic price method (HPM) has been widely used in studies of commodity prices [21–32], and its use is particularly appropriate in contexts that entail heterogeneous production inputs whose underlying production characteristics demonstrate significant variations. Given differences in forest characteristics, including component tree species and their quality, size, or volume, forest assets are evidently heterogeneous commodities. From the perspective of wood producers, a forest is a typical heterogeneous product, entailing complex inputs evidencing diverse characteristics.

Some researchers outside China have applied the HPM to study forest assets or services. Escobedo et al. [33] conducted a valuation of an urban forest ecosystem service by integrating an explanatory hedonic regression model with randomly measured field data on trees, shrubs, and turf compiled for four cities in the US state of Florida during the period 2006–2009. Puttock et al. [34] estimated the price of standing timber in the southwestern part of the Canadian province of Ontario using this method. Their results indicated that volume, species composition, tree size, timber quality, and distance to the purchasing mill were important characteristics influencing stumpage prices. Aronsson et al. [35] found that the market value of the stumpage per hectare was negatively related to the area of its occurrence and positively related to the stock volume. In addition, the incomes of sellers and buyers respectively have positive and negative effects. Leefers et al. [36], who estimated stumpage prices in the Lake States forests in the United States, found that stumpage prices were aligned with the identities of individual species. In a study of 4824 standing timber sales transactions conducted during the period 2008–2012, Kolis et al. [37] analyzed the relationship between stumpage prices and sales-specific factors. Their findings revealed the impacts of seasonal harvest restrictions, sales volumes, timber assortment, and forest damage on stumpage prices. Kim et al. [38], who analyzed the relationship between pine stumpage prices and associated sales characteristics, found that increases in these prices corresponded to increases in the sales volumes, contract length, bid sales, and the number of bidders. Moreover, a positive relationship existed between higher timber grades and better market and logging conditions and stumpage prices.

The differences between predictive models developed by previous researchers to investigate stumpage prices are mainly reflected in different driving factors and regression coefficients. These differences can be attributed primarily to variations in regional market environments and data characteristics. The novelty of forestry exchange markets, small sample sizes, and incomplete data are primary reasons explaining the dearth of studies on stumpage prices in China. However, a review of stumpage prices would shed light on changes in the trend of stumpage prices and advance understanding of the main factors that positively or negatively affect stumpage prices and forest assets in different regions of China. This will allow the values of standing trees to be evaluated and predicted.

The HPM can be used to construct a quality-adjusted price index (a hedonic price index) that reflects the price change trend and the degree of change. This index reveals the supply and demand relationship within a market. Traditional indexes that depend on mean or median prices may be less accurate and robust when applied to heterogeneous goods. The hedonic price index is an appropriate index for use with heterogeneous commodities and has been widely applied within the real estate [39–43] and art [44–46] markets, and in relation to products such as computers [47–49] that reflect rapid technological changes. This index can be implemented using different approaches, for example, the dummy time hedonic (DTH) index and the hedonic imputation (HI) index [50–53]. The dummy time method is the original approach used to construct a quality-adjusted price index and has a wide range of applications, whereas the imputation method entails the application of standard price index formulas, such as the Laspeyres and Paasche indexes. Since China has an active timber market and its timber products have standard specifications, a price index could be compiled using traditional methods. A state-level price index, based on the Guangdong Yuzhu International Timber Market—China's largest market for timber products—was published in 2012. However, because standing trees are heterogeneous commodities and the forestry exchange market is relatively new, an index for stumpage prices remains to be established. The compilation of such an index can advance understanding of the change trend relating to stumpage prices. However, computation of the Laspeyres and Paasche price indexes is difficult to perform in the context of stumpage. Therefore, in this study, we applied the dummy time method to construct a quality-adjusted stumpage price index.

Chinese fir is one of the most important fast-growing tree species in China. At present, the area of Chinese fir plantations is 17×10^{6} ha, accounting for 24% of China's planted forest area [54]. As the most important timber species in southern China, the Chinese fir timber forest is the main transaction target of the forestry exchange market in this region. In the current management process, due to the emphasis on fast-growth, high-yield, and intensive management, Chinese fir timber forests are often single species structures.

This study had the following primary objectives. The first was to establish a model for forecasting the stumpage prices of Chinese fir timber forests and to compile sequential price and base price indexes for the stumpage prices of Chinese fir timber forests. The second was to elucidate the changing trend for stumpage prices over a 10-year period and to analyze the relationship between stumpage prices and the sales characteristics of Chinese fir timber forests. The third and final objective was to compare the price changes in the forestry exchange markets and the timber markets and to evaluate the uncertainty and risks associated with these two markets.

2. Materials and Methods

2.1. Data Collection

China's forestry exchange markets entail two forms of trading: floor trading and over-the-counter trading. Whereas statistics on over-the-counter trading were difficult to procure, we were able to obtain relatively comprehensive information on trading volumes and the amount of floor trading. The floor trading data presented in this paper were obtained from the South China and East China Forestry Exchanges, both of which are primary markets for forest trading in collective forest areas in Southern China. These forests are located within a vast expanse of land stretching from south of Qinling and Huaihe to east of the Yunnan-Guizhou Plateau. This region encompasses 10 provinces: Hunan, Hubei, Jiangxi, Anhui, Zhejiang, Fujian, Guangdong, Guangxi, Hainan, and Guizhou. The forested area is characterized by a warm climate, abundant rainfall, good plant growth conditions, and a wide variety of tree species. The main tree species found within plantation forests are Chinese fir and Masson pine. This region is China's main wood production base, accounting for 37.12% of the country's forest area. Most of the forests and forest land in Southern China are collectively owned.

The floor trading data from the forestry exchange markets included region, project type, ownership type, stand structure, stand age, stand stock volume, forest species, transfer period, forest land area, transaction date, and transaction price (Table 1). However, because China's forestry exchange markets were in the initial stage of development, many transaction data were incomplete.

Table 1. Illustrative sales data procured from forestry exchange markets in China.

Fields	Expected Sign	Examples
Location		Chengjia Dock, Fangpo Village, Suzhuang Town, Kaihua County, Quzhou City, Zhejiang Province.
Type		Ownership of standing trees
Ownership		Collective ownership
Distance to nearest simple road (km)	-	2
Distance to nearest national, provincial or county roads (km)	-	20
Structure	+/-	70% Chinese fir + 30% Masson pine
Age (year)	+	20
Age group	+	mature age
Category	+/-	timber forest
Transfer period (year)	+/-	5
Area (ha)	+/-	11.67
The average diameter at breast height (cm)	+	17.4
The average high (m)	+	12.5
Volume ($m^{3)}$	+	Chinese fir-333 m^3, Masson pine-143 m^3, total- 476 m^3
Total price (10^4RMB)		18.7
Transaction date		2017.7.21

The trading assets of the South China and East China Forestry Exchanges were mainly located in collective forest areas within Southern China (Figure 1). Within this region, Jiangxi Province accounted for the highest number of trading transactions that mostly involved standing trees, followed by the provinces of Zhejiang and Hunan. Although the number of deals has increased, China's forestry exchange markets are still in their infancy and are likely to remain so for a long period of time. Consequently, issues such as nonstandard, incomplete, and untimely information disclosure arose especially during the initial years. In many cases, only limited information on, for example, the time of the trading, trading volume, stand age, forest land area, and total stock volume was procured. In recent years, a gradual improvement in the recording and standardization of information in China's forestry exchange markets has been evident. In some instances, important location information, such as location maps and the distances of forests from simple forest, national, and provincial roads have also been noted. However, records that contain complete transaction information are still relatively sparse.

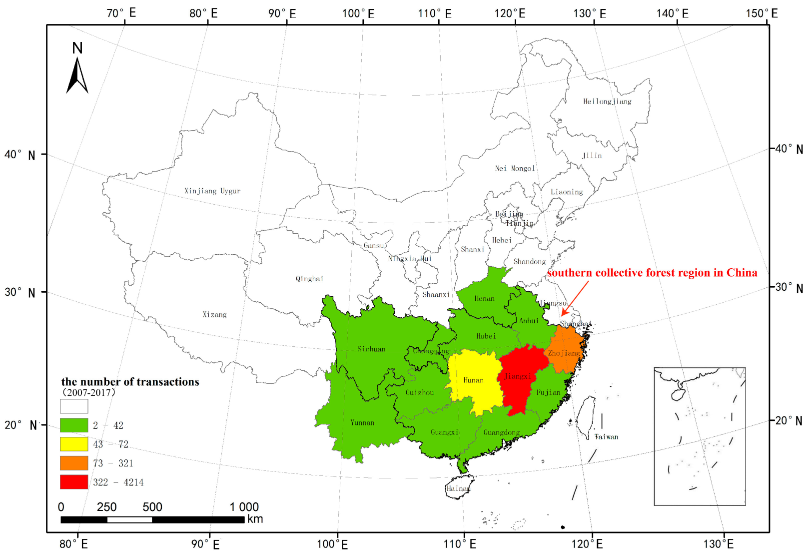


Figure 1. A map showing the distribution of sales transactions in China.

2.2. Hedonic Price Method

The HPM was first introduced by Waugh [55] and began to attract serious attention in the 1970s [56]. Rosen [57] proposed a comprehensive theoretical framework for analyzing hedonic pricing in 1974. This framework enabled the relationship between price and commodity characteristics to be clarified and led to the formulation of a theoretical system for analyzing heterogeneous products. The HPM is based on the premise that the price of a good is related to its characteristics or to the services that it provides. It enables the implied value of characteristics to be estimated from the value of the price of goods using regression analysis. The following hedonic price model, entailing a dummy time element was applied in this study:

$$P_t = \beta_0 + \beta_t d_t + \sum_{k=1}^{m} \beta_k x_k + \varepsilon \quad (1)$$

where, P_t denotes the price for time period t, β_0 is an estimate of the constant, β_t is the coefficient estimate of the time variable that directly reflects the impacts of changes in prices over time, and d_t is the dummy time variable. When t is the base period, d_t = 0; when t is the reporting period, d_t = 1. β_k is the coefficient estimate of a characteristic k (1,…,m), x_k is a characteristic k (1,…,m), and ε is the error term component.

The linear form of the model is the most widely used form. However, quantitative dependence among variables is commonly encountered in attempts to model actual social and economic activities and is expressed as non-linear equations. Therefore, in addition to the basic linear form, logarithmic and semi logarithmic functions were also expressed. The three basic forms of the model are as follows:

(1) Linear form:

$$P_t = \beta_0 + \beta_t d_t + \sum_{k=1}^{m} \beta_k x_k + \varepsilon \quad (2)$$

In Equation (2), the independent and dependent variables are inserted into the linear form of the model, and the regression coefficient corresponds to the price of the feature.

(2) Semi logarithmic form:

$$\ln P_t = \beta_0 + \beta_t d_t + \sum_{k=1}^{m} \beta_k x_k + \varepsilon \quad (3)$$

In Equation (3), the independent variable is linear, the dependent variable is logarithmic, and the regression coefficient corresponds to the rate of price change.

(3) Double logarithmic form:

$$\ln P_t = \beta_0 + \beta_t d_t + \sum_{k=1}^{m} \beta_k \ln x_k + \varepsilon \quad (4)$$

In Equation (4), the independent and dependent variables are inserted into the model as logarithms, and the regression coefficient corresponds to the price elasticity of these features. Thus, providing that other features remain unchanged, for every one percentage point change in a feature variable, there will be a corresponding change in the characteristic price.

2.3. Dummy Time Hedonic Index

The DTH index is an approach used to estimate price changes. Compared with the HI index, the DTH index does not require a matched sample [50]. The DTH index is established on the basis of a hedonic price model. While excluding the influence of changes in feature variables on the price, this index reflects changes in the market price that are associated with the passage of time. Since this method requires a constant time interval to be maintained between the base period and the reporting periods that are not overly long, we constructed the price index with annual data.

The sequential price index and the base price index were constructed as follows:

(1) Sequential price index:

$$I_t = e^{\widehat{\beta}_t} \tag{5}$$

(2) Base price index:

$$I'_t = I_t \times I_{t-1} \times I_{t-2} \cdots\cdots \times I_1 \tag{6}$$

where, I_t is the t-period sequential price index, I'_t is the t-period base price index, and $\widehat{\beta_t}$ is a parameter estimate in the hedonic price model.

3. Results

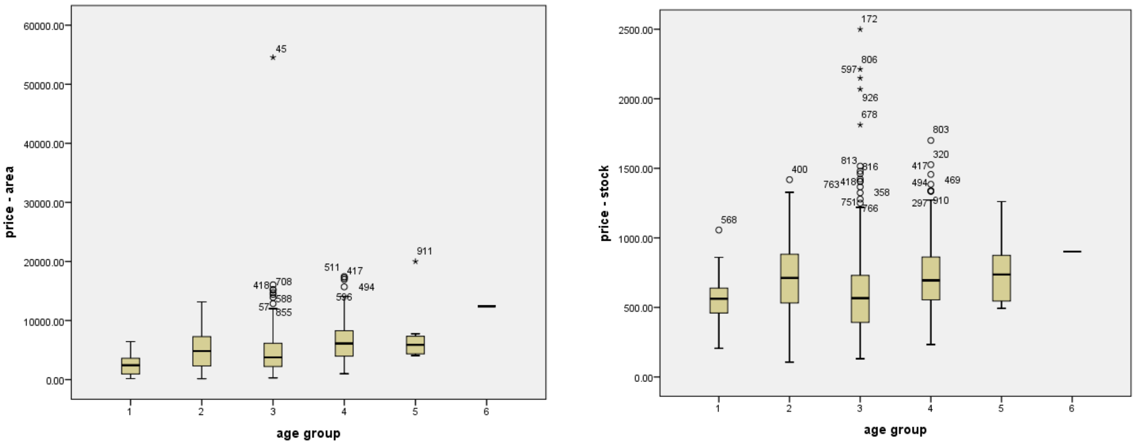
3.1. Actual Stumpage Prices of Chinese Fir Timber Forests

After we had excluded incomplete and abnormal data, a total of 928 completed sales transactions of pure Chinese fir timber forests remained for inclusion in the analysis. Since there were significant variations in the prices of standing trees of different ages, we divided the tree age into six groups according to group distance d = 10 (Table 2). The statistical results indicated that the trading volume in the 20–30 group was the greatest, followed by the 10–20 and 30–40 groups. The average prices per cubic meter and per hectare were 599.52 yuan/m^3 and 4483.37 yuan/ha respectively. Compared with the price per unit area (yuan/ha), the price per unit volume (yuan/m^3) was more discrete, with more outliers occurring in the 20–30 and 30–40 groups (Figure 2).

Table 2. Unit prices of forests of Chinese fir timber belonging to different age groups.

Age Group (year)	Trading Volume (case)	Average Price Unit Stock Price (yuan/m^3)	Unit Area Price (yuan/ha)
0–10	13	574.6199	2638.0159
10–20	142	714.6930	4872.8164
20–30	601	599.5162	4483.3684
30–40	161	736.7439	6571.9358
40–50	10	689.4719	6699.8284
other	1	901.4534	12404.0000
total	928	641.8940	4911.8777

Age Group (year)	Unit Stock Price (yuan/m^3)		Unit Area Price (yuan/ha)	
	min	max	min	max
0–10	206.0687	1056.4235	162.4129	6442.8945
10–20	106.6666	1418.4397	147.3414	13,157.8947
20–30	131.1991	2500.0000	284.3601	54,545.4545
30–40	233.3816	1700.5128	982.3736	17,439.3305
40–50	98.4009	1260.6599	487.8048	20,000.0000
other	901.4534	901.4534	12,404.0000	12,404.0000
Total	98.4009	2500.0000	147.3414	54,545.4545



(**a**) Unit area prices (**b**) Unit stock prices

Figure 2. Box plots of unit prices of forests of Chinese fir trees by area (**a**) and stock (**b**).

3.2. Selection of a Hedonic Price Model for Chinese Fir Timber Forests

At the time of our study, China's forestry exchange market was at a nascent developmental stage, characterized by insufficient competition and incomplete information disclosure. Constraints relating to data collection made it impossible to construct a hedonic price model that included all of the characteristic variables. However, a preliminary analysis could still be performed using existing data. Whereas the available data on stand ages, forest land areas, and stock volumes were definite and complete, other indexes, such as the average diameter at breast height (DBH), average tree height, and distance to the nearest road were often absent. Therefore, we only included the three definite variables in our study.

Considering the actual transaction price (i.e., the total price) as a dependent variable and the stand age, forest land area, and total stock volume as independent variables, the linear, semi logarithmic, and double logarithmic forms were used for the estimations. The results of the analysis indicated that there was a high goodness of fit for the linear and double logarithmic models ($R_{ad}^2 \geq 80\%$), whereas the R_{ad}^2 of the semi logarithmic model was only 27.8%, indicating a relatively low goodness of fit (Table 3; Table 4. In the linear and double logarithm models, the variable of forest land area failed to pass the significance test. The prediction effect and accuracy of the three forms were evaluated using the standard error. The results showed that the prediction error of the double logarithm form was the smallest. To further analyze the prediction effect of the double logarithm form, data on 30 cases outside the model were used for prediction in this paper. An independent sample *t*-test was carried out on the two groups of data of the actual stumpage price and the predicted stumpage price (Table 5). The results showed that $p > 0.05$, indicating that there was no significant difference between the mean values of the two groups.

Table 3. Model setting. Sig.: significance.

Model		SS	df	MS	F	Sig.
1	Regression	8,381,455.863	3	2,793,818.621	2109.826	0.000^{***}
	Residuals	1,185,153.470	895	1324.194		
	Total	9,566,609.333	898			
2	Regression	352.851	3	117.617	116.412	0.000^{***}
	Residuals	904.267	895	1.010		
	Total	1257.117	898			
3	Regression	1071.793	3	357.264	1725.365	0.000^{***}
	Residuals	185.324	895	0.207		
	Total	1257.117	898			

Notes: (1) Models 1, 2, and 3 represent linear, semi logarithmic, and double logarithmic models, respectively. (2) *** $p \leq 0.001$.

Table 4. Model statistical test.

Model		Coefficients					
		B	Std. Error	Beta	*t*	Sig.	
1	Constant	7.007	3.331		2.104	0.036	R^2_{ad} = 0.876 Std. Error = 36.389
	Age	0.516	0.126	0.048	4.093	0.000 ***	
	Volume	0.045	0.001	0.916	58.696	0.000 ***	
	Area	0.008	0.005	0.022	1.426	0.154	
2	Constant	3.024	0.092		32.873	0.000	R^2_{ad} = 0.278 Std. Error = 1.005
	Age	0.014	0.003	0.116	4.085	0.000 ***	
	Volume	0.000	0.000	0.381	10.122	0.000 ***	
	Area	0.001	0.001	0.172	4.589	0.000 ***	
3	Constant	−3.439	0.146		−23.626	0.000	R^2_{ad} = 0.852 Std. Error = 0.455
	Age	−0.023	0.038	−0.008	−0.591	0.555	
	Volume	1.102	0.027	0.932	40.969	0.000 ***	
	Area	−0.010	0.026	−0.009	−0.396	0.692	

Notes: *** $p \leq 0.001$.

Table 5. Independent sample *t*-test for Model 3.

Group	N	Mean	Std. Deviation	Std. Error Mean
1	30	3.1614	1.1510	0.2101
2	30	3.5895	1.0194	0.1861
	t value	df	Sig.(2-tailed)	
	−1.525	58	0.133	

Notes: Group 1 = ln (actual stumpage price), Group 2 = ln (predicted stumpage price).

3.3. Determination of the Hedonic Price Method for Chinese Fir Timber Forests

In the equations expressing the linear and double logarithmic models, the influence of forest land area on price was not significant. We, therefore, excluded this variable. The nature and correlation of data did not change following the inclusion of logarithms, but the scale of the variable was compressed, and the data were found to be more stable. Consequently, we selected the model with the double logarithm form. The predictive models, entailing a dummy time element were established on the basis of continuous annual data obtained for the period 2007–2016 (Table 6).

Table 6. The annual forecast model.

Year	Model	Test
2008	$\ln\hat{P}_{2008} = -4.346 + 0.155d_{2008} + 0.097\ln age + 1.093\ln stock$ t = (−11.263) (1.730) (0.988) (34.455)	n = 170, sigF = 0.000 ***, R^2_{ad} = 88%, Std.Error = 0.414
2009	$\ln\hat{P}_{2009} = -4.116 + 0.059d_{2009} + 0.027\ln age + 1.114\ln stock$ t = (−9.427)(0.996)(0.206)(35.535)	n = 260, sigF = 0.000 ***, R^2_{ad} = 83.8%, Std.Error = 0.462
2010	$\ln\hat{P}_{2010} = -3.562 + 0.588d_{2010} - 0.027\ln age + 1.060\ln stock$ t = (−11.502)(8.560)(−0.346)(29.802)	n = 207, sigF = 0.000 ***, R^2_{ad} = 86.5%, Std.Error =0.446
2011	$\ln\hat{P}_{2011} = -2.494 - 0.040d_{2011} + 0.020\ln age + 0.969\ln stock$ t = (-11.330)(−0.839)(0.459)(36.965)	n = 200, sigF = 0.000 ***, R^2_{ad} = 87.5%,

		Std. Error = 0.333
2012	$\ln\hat{P}_{2012} = -2.381 - 0.001d_{2012} - 0.097\text{lnage} + 0.998\text{lnstock}$ t = (−14.552)(−0.032)(−2.483)(50.935)	n = 276, sigF = 0.000 ***, R^2_{ad} = 90.6%, Std. Error = 0.308
2013	$\ln\hat{P}_{2013} = -2.608 + 0.077d_{2013} - 0.147\text{lnage} + 1.053\text{lnstock}$ t = (−15.591)(1.975)(-3.257)(56.460)	n =2 49, sigF = 0.000 ***, R^2_{ad} = 93, Std. Error = 0.283
2014	$\ln\hat{P}_{2014} = -3.389 + 0.071d_{2014} + 0.184\text{lnage} + 1.021\text{lnstock}$ t = (−13.027)(1.554)(2.319)(43.665)	n = 148, sigF = 0.000 ***, R^2_{ad} = 93.8%, Std. Error = 0.272
2015	$\ln\hat{P}_{2015} = -3.534 - 0.288d_{2015} + 0.343\text{lnage} + 0.9751\text{lnstock}$ t = (−8.913)(−6.180)(2.861)(38.544)	n = 114, sigF = 0.000 ***, R^2_{ad} = 93.7%, Std. Error = 0.246
2016	$\ln\hat{P}_{2016} = -5.044 + 0.058d_{2016} + 0.698\text{lnage} + 0.982\text{lnstock}$ t = (−9.365)(1.136)(4.252)(37.748)	n = 98, sigF = 0.000***, R^2_{ad} = 94.3%, Std. Error = 0.251

The results obtained using this model indicated that the stock volume had a significant impact on stumpage prices, and the p-value of the regression coefficient significance test conducted for each year was less than 0.001. The influence of stand age on stumpage prices was small, but it gradually increased and became significant after 2011. Apart from the characteristic variables, the transaction timing, especially within models constructed in 2010 and 2015, also affected the stumpage prices. The result of the regression coefficient test for the dummy time variable was $p < 0.001$, indicating a drastic change in the price compared with the changes in 2009–2010 and 2014–2015. The changes in the R^2_{ad} and standard error values reflected improvements in the model. Specifically, the predictions estimated closer points in time, revealing that the Chinese fir stumpage prices were gradually returning to rational values with the introduction of the Chinese forestry exchange market, and gradually progressing toward standardization.

In addition, the model was tested for economic significance. Taking the model of 2016 as an example, the price elasticity of the stock volume was 0.982, that is, for every 1% increase in the stock volume, the average stumpage price increased by 0.982%, and the price elasticity of the stand age was 0.698, that is, every 1% increase in stand age, the stumpage price increased by 0.698% on average. The coefficient symbol and size were in line with expectations.

In order to further explain the influence of the change of these two variables on the change of stumpage price, this paper selected the most recent predicted model, namely the model of 2016 (see Table 6), to carry out the single factor sensitivity analysis on the stock volume and stand age. Among the 928 sample data, the value range of stock volume was (51,600, [17]) while the stand age range was [1,44]. The mean of stock volume was close to 1200 m^3 while that of the stand age was close to 20 years. Hence, the stock volume was fixed at the level of 1200 m^3, the stumpage prices at a stand age of 5, 10,…, 35, and 40 (8 groups in total) were predicted and the sensitivity coefficients of stand age were calculated. In the meantime, the stand age was fixed at the level of 20 years, the stumpage prices when the stock volume was 5000, 10,000,..., 45,000, and 50,000 (10 groups in total) were predicted and the sensitivity coefficients of stock volume were calculated (Table 7; Table 8). The results showed that compared with the stand age, the stumpage price was more sensitive to the stock volume and the stock volume was a very important factor affecting the stumpage price.

Table 7. Sensitivity analysis of stock volume.

Age (year)	Stock (m^3)	△Stock/Stock	Price (10^4 yuan)	△Price/Price	Sensitivity
20	5000	-	237.20	-	-

20	10,000	1	468.52	0.98	0.98
20	15,000	2	697.67	1.94	0.97
20	20,000	3	925.42	2.90	0.97
20	25,000	4	1152.14	3.86	0.97
20	30,000	5	1378.03	4.81	0.96
20	35,000	6	1603.25	5.76	0.96
20	40,000	7	1827.89	6.71	0.96
20	45,000	8	2052.02	7.65	0.96
20	50,000	9	2275.70	8.59	0.95

Notes: △Stock/Stock = ($Stock_i$- $Stock_1$)/ $Stock_1$, △Price/Price = ($Price_i$- $Price_1$)/$Price_1$, i = 2,3,…,10. Sensitivity = (△Price/Price)/(△Stock/Stock).

Table 8. Sensitivity analysis of stand age.

Age (year)	Stock (m^3)	△Age/Age	Price (10^4 yuan)	△Price/Price	Sensitivity
5	1200	-	22.19	-	-
10	1200	1	36.01	0.62	0.62
15	1200	2	47.78	1.15	0.58
20	1200	3	58.41	1.63	0.54
25	1200	4	68.25	2.08	0.52
30	1200	5	77.52	2.49	0.50
35	1200	6	86.32	2.89	0.48
40	1200	7	94.75	3.27	0.47

Notes: △Age/Age = (Age_i- Age_1)/ Age_1, △Price/Price = ($Price_i$- $Price_1$)/$Price_1$, i = 2,3,…,8. Sensitivity = (△Price/Price)/(△Age/Age).

3.4. Index of Stumpage Prices of Chinese Fir Timber Forests

The DTH index was used to compile sequential and base price indexes for Chinese fir timber forests. The results of the study revealed that the price of these forests changed significantly in 2010 and 2015. The price index in 2015 was 74.95%, implying that the price in 2015 decreased on average by 25.05% compared with the price in 2014. The price index in 2010 was 180.01%, implying that the price in 2010 increased by 80.01% on average compared with the price in 2009 (Table 9, Figure 3). Taking 2007 as the base period for calculating the base price index of Chinese fir timber forests, I_{2016} = 197.00%, indicating that the price in 2016 had increased by 97% compared with the price in 2007, evidencing an average annual growth rate of 7.82% (197.00%$^{1/9}$-1).

Table 9. The Stumpage Price Index of Chinese fir timber forests.

Year	$\widehat{\boldsymbol{\beta}_t}$	I_t (Sequential)	I_t (Base- 2007)
2016	0.058	105.99%	197.00%
2015	−0.288	74.95%	185.87%
2014	0.071	107.36%	247.99%
2013	0.077	107.99%	230.99%
2012	−0.001	99.87%	213.90%
2011	−0.04	96.08%	214.18%
2010	0.588	180.01%	222.92%
2009	0.059	106.07%	123.84%
2008	0.155	116.75%	116.75%

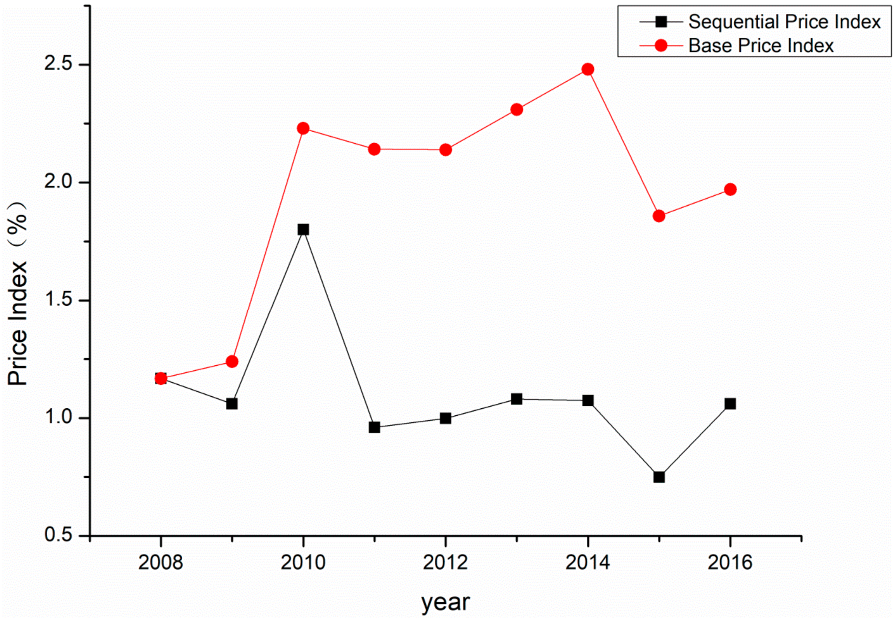


Figure 3. The chart of the stumpage price index of Chinese fir timber forests.

4. Discussion

4.1. Choice of HPM Form

Since variables with different scales as well as dummy variables were selected, we needed to find the optimal model form, e.g., linear, semi logarithmic, double logarithmic, or other forms. No one form is the best for every situation. The best form depends on which is more suitable for your actual situation [58,59]. Previous studies on the stumpage price have generally adopted the linear form of HPM [15,37]. In this paper, the linear form also had a good predictive power, but the model comparison revealed that the double logarithmic form was best suited for our research.

4.2. Factors Driving Stumpage Prices of Chinese Fir Timber Forests

Stock volume was the key driver of stumpage prices of Chinese fir. Munn et al. [60] found that when stumpage values were positive, the predicted signs of the coefficients of volume variables were all positive. Our results indicated that there was a strong positive correlation between stock volume and the stumpage prices of Chinese fir. The effects of forest management are ultimately reflected in tree volume and growth. If the volume of a stand is high, then the forest harvest and corresponding incomes of forest farmers will be high. Therefore, the value of forest assets is mainly reflected in the value of trees. In addition, while China's forest law allows for the mortgage of timber forests, a forest asset evaluation must first be conducted. The valuation of standing trees is mainly conducted using two methods: the replacement cost method and the present value of benefits method. While the former is only applicable to young forests, the latter is applicable to stands of other ages, and the main parameter used is the stock volume.

The effect of stand age on the stumpage prices of Chinese fir was less than that of stock volume, and there was also a positive correlation between stand age and stumpage price. Zhang et al. [61] found that the age of pine had a significant impact on the price of timber stands. In timber forests, volume growth, which is closely related to tree height and DBH, is an important index of stand quality management. Average DBH and stand height are also important indexes for evaluating stand quality. According to the findings of previous studies, a close positive correlation exists between the stand age and the mean DBH, mean tree height, or basal area. Accordingly, age–height and age–DBH growth models have been established [62,63]. Stand age is an important criterion in the study of stand growth dynamics, stand biomass change, and site quality.

The results of this study indicated that there is no correlation between the forest land area and the stumpage prices of Chinese fir. A probable reason for this finding is that our study focused on the price of standing trees and not on the forest land. From the perspective of buyers of forest assets, the purchase price is affected by the number of trees and not by the area of forest land.

4.3. The Difference between Forestry Exchange and Timber Markets in China

The DTH index method, which was used to compile the stumpage prices index, has practical application value. An index of stumpage prices reflects the price change degree and trend and provides a basis for establishing the price considering both buyers and sellers in the forestry exchange market. A comparison of the price change trend of standing trees in the forestry exchange market and log prices in the timber market can shed light on the differences between these two markets. Our results indicated that between 2015 and 2010, the stumpage prices of Chinese fir in the forestry exchange market changed significantly, as evidenced by price indexes of 74.95% in 2015 and 180.01% in 2010. To compare the stumpage and log prices, we collected the annual prices of Chinese fir logs from Lechang in Guangdong Province that were 4 m long, with tail diameters of 5–6 cm and 9–10 cm, respectively, for the period stretching from 2007 to the end of 2016. The prices of logs with a tail diameter of 5–6 cm, expressed in yuan/m^3, were as follows: 660, 500, 600, 700, 860, 950, -, 980, 1050, and 1020, while the prices of logs (in yuan/m^3) with a tail diameter of 9–10 cm were 750, 560, 700, 900, 960, 1050, -, 1100, 1150, and 1120 (http://www.chinatimber.org). This comparative analysis reveals differing price changes relating to Chinese fir in the two markets. In 2015, the growth rate of the prices of logs with tail diameters of 5–6 cm and 9–10 cm were 7.14% and 4.55%, respectively, whereas the growth rate of stumpage prices was −25.05%. In 2010, the growth rate of prices of logs with tail diameters of 5–6 cm and 9–10 cm were 16.67% and 28.57%, respectively, whereas the growth rate of stumpage prices was 80.01%. Thus, the forestry exchange and timber markets evidenced significant differences. The price range within the timber market was relatively small, whereas the price range within the forestry exchange market was relatively large. This finding indicates that there are more uncertain factors and risks in the forestry exchange market compared with those existing in the timber market.

4.4. Impact on Forest Accounting

We developed an alternative approach for estimating the market value of standing trees that differs from previous forest accounting approaches recommended within the System of Integrated Environmental and Economic Accounting (SEEA), proposed by the United Nations [64,65]. The SEEA is based on the net present value method, the stumpage value method, and the consumption value method. Whereas the net present value method is greatly influenced by the discount rate, in the latter two methods, the value of standing trees is obtained by multiplying the standing volume by the price of timber of the kind being produced and sold in the timber market. These three methods cannot reflect the stumpage market value of standing trees or provide a value scale for fair market transactions. In the context of the SEEA initiative (SEEA 2012), in 2014, the Chinese government announced that it would prepare national and local balance sheets of natural resources [66]. The purpose of these balance sheets, entailing an accounting period coinciding with the calendar year from 1 January to 31 December, was to contribute to China's efforts to promote sustainable development through an assessment of changes in the physical quantity and monetary value of natural resource assets during the year in question. However, so far, there has been no substantial progress in the preparation of natural resources balance sheets, with the accounting method posing major technical difficulties. The annual prediction model constructed in this paper provides an approach for conducting batch and periodic assessments of forest resources.

4.5. Further Studies

Data collection was a key constraint in the model-building process. We examined only four variables relating to stumpage prices: volume, age, area, and the time of trading and did not consider factors such as location, distance from adjacent roads, and cutting costs. Future studies could extend these variables by adjusting and adding other variables. Additionally, we only assessed the stumpage prices of Chinese fir timber forests, and did not examine other forest types and tree species. With the development of the forestry exchange market in China, more in-depth research will be required.

5. Conclusions

We investigated the change trend and driving factors of stumpage prices of Chinese fir timber forests using the HPM and DTH index. The stock volume was the most important factor, followed by the age of the stand. The area of the forest had no significant effect on the stumpage price. It should be noted that although the independent variables assessed in this study were limited, the proportion of the variation of the dependent variable that could be explained by independent variables was over 80% ($R_{ad}^2 > 80\%$, which meant that the explanatory power of statistical model was strong. In addition, we found that compared with the timber market, the forestry exchange market is more volatile and uncertain. This study encompassed the perspectives of buyers as well as sellers within forestry exchange markets thus providing valuable inputs that can facilitate the efforts of the Chinese government to optimize resource allocation and direct the forestry exchange market toward standardization.

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