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Original Paper

Monthly Sales Forecast of Cigarettes under the Background of Business and Finance Integration

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Abstract

Developing accurate and effective sales plans is of great value to every enterprise. This article takes the cigarette marketing line in L region as the research object, and develops a monthly sales model that matches the actual situation and has guiding value. The monthly sales forecast is constrained by annual sales and experience, resulting in two main problems: low planning accuracy and large fluctuations in actual monthly sales, making modeling difficult. Through research, it has been found that the fluctuations between different years and the same month are relatively small compared to the annual fluctuations. Therefore, it has been decided to adopt three types of exponential smoothing models: simple equilibrium, Hote linearity, and Brownian trend to predict monthly sales. By comparing three models, the Hote linear model predicts results more accurately.

Keywords

Exponential Smoothing Monthly Plan Hote Linear Brownian Trend

1. Introduction

The integration of business and finance is one of the important research contents in the financial field. How to integrate business and finance, and the accuracy of integration have a profound impact on the high-quality development of enterprises. It can guide enterprises to allocate resources, optimize their business structure, and continuously cultivate and expand competitive advantages in fierce market competition. The integration of business and finance, business is the foundation, and the accuracy of business volume prediction directly affects the accuracy of financial budgeting. Only with accurate business prediction can business and finance integration have the foundation for integration, until further integration of business and finance elements and models promotes high-quality development of enterprises. Only with accurate business prediction can business and finance integration have the foundation for integration, until further integration of business and finance elements and models promotes high-quality development of enterprises. Accurately predicting future development trends is a highly valuable thing for all industries. It can not only guide current organizations and individuals to effectively complete their current tasks, but also has greater significance in utilizing the effective leverage of economic development in the increasingly complex market competition to achieve development goals or guide innovation breakthroughs. Sales forecasting is a key aspect of forecasting, as its accuracy plays a decisive role in determining key competitive advantages and processes for enterprises in dynamic and intense market competition. At the micro level, it guides enterprises to take market demand as a guide, prepare specific task plans in advance for procurement, warehousing, processing and manufacturing, personnel recruitment, research and development investment, and build an advantageous supply chain to ensure that enterprises obtain long-term competitive advantages.

2. Research on Smooth Model Literature

Li Na and Zheng Shaozhi (2018) used non parametric smoothing methods to predict China's stock market[1]; Lian Jin (2019) fitted the trend of ship flow using first-order exponential smoothing and second-order exponential smoothing[2]; Zhang Beibei, Li Jingwen, and Yang Yanan (2019) used a combination of multi parameter exponential smoothing models to predict the value growth rate of Zhongguancun[3]; Feng Xing, Lin Dandan, Li Aiqiao et al. (2020) established a time series model using the HOLT dual parameter exponential smoothing method to predict the incidence trend of sheep brucellosis in the next two years[4]; Huang Weijian, Zhang Yifan, and Huang Yuan (2020) studied the dynamic cubic exponential smoothing model with dynamic smoothing coefficients and parameters to predict the power generation of thermal power plants[5]; Yang Yi, Wei Yan, Huang Xiaoling et al. (2020) used exponential smoothing method to predict magnetic resonance imaging demand in medical institutions [6]; Han Yonggui, Han Lei et al. (2021) used exponential and ARIMA models to screen for the optimal step size and prediction step size, and predicted the saturated water vapor pressure difference in the northwest region[7]; Bao Yanke, Chen Ran et al. (2022) studied the overnight position prediction of index smoothing and autoregressive fusion prediction models in banking business[8]; Ilizati Aireti (2022) used exponential smoothing model and conditional heteroscedasticity model to predict the Chinese consumer price index[9]; Wu Di, Ma Wenli, and Yang Lijun (2023) proposed a quadratic exponential smoothing multi-objective combination model for predicting power load[10]..

Exponential smoothing is a widely used method in time series prediction and has a wide range of applications. From current research, it can be seen that exponential smoothing and exponential smoothing composite models have been applied in various fields such as finance, shipping, disease prevention, air pressure, and consumption, and the prediction results are relatively ideal. From a series of studies, it has been found that the accuracy and precision of exponential smoothing prediction results are related to the smoothing coefficient α The correlation between values is very high, so choosing a scientific and adaptive smoothing method is of great significance.

3. Current Situation and Existing Problems of Monthly Sales Forecast in L Region

3.1 Current Status of Monthly Sales Forecast

L region is an important consumption area for cigarettes in Sichuan Province, with high annual cigarette sales and high value. Due to the strong consumption characteristics of cigarettes, multiple factors must be considered when formulating annual cigarette sales, and the profit level of tobacco enterprises cannot be taken into account.

Every year, an annual and monthly sales plan is formulated for the following year. The main method of planning is to determine the total sales volume and monthly sales volume for the following year based on the previous year's sales, experience, and tax and profit factors. Taking Sichuan as an example, there are hundreds of cigarette brands in each city, and economically developed cities have more cigarette brands, with significant differences in prices. Different brands meet the needs of consumers at different levels. As cigarettes are a necessity and dominate tobacco companies, when formulating annual sales plans, it is necessary to consider the demand of consumers at different levels, rather than solely focusing on economic benefits. Therefore, the factors considered in cigarette sales plans are diverse and complex, and the corresponding monthly sales plans are also affected by corresponding factors. In the actual preparation of annual and monthly sales plans, decisions are mostly based on historical data and experience.

3.2 Problems in Monthly Sales Forecast

(1) The accuracy of monthly sales plan is not high. One of the goals of planning is to avoid significant fluctuations in production and sales, resulting in resource imbalance. However, due to changes in consumer demand, demand time, and demand scenarios, there are significant differences between actual sales and plans, leading to poor accuracy of monthly sales plans.

(2) The large fluctuations in actual monthly sales make modeling difficult. The existence of Yuanchun and regional festivals results in a significant difference in sales between January and February throughout the year. If December of the year is compared together, the difference in monthly sales is more pronounced, as shown in Figure 1. The sales trend changes repeatedly, making it difficult to predict monthly sales with an accurate model.

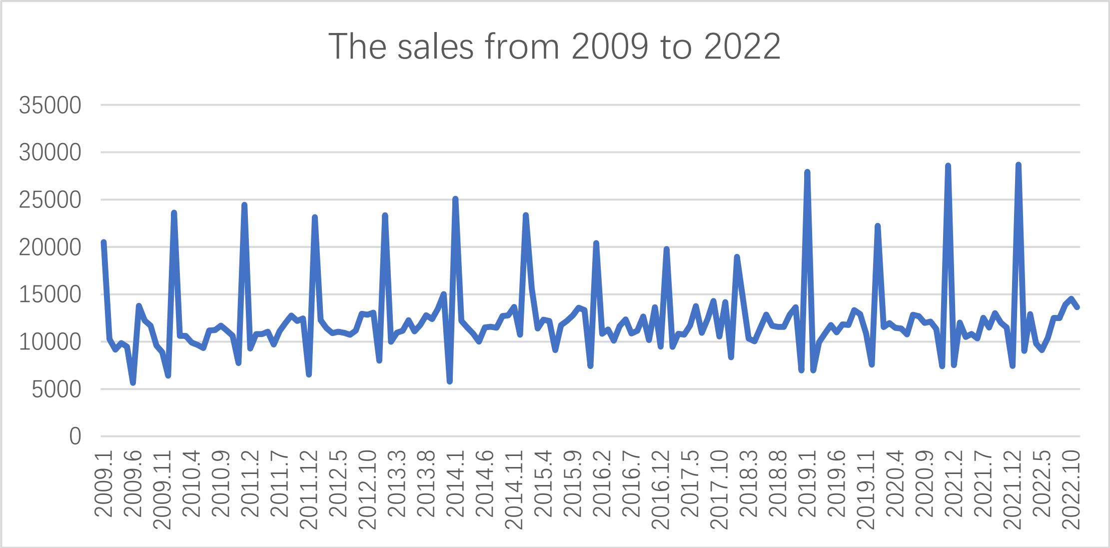

Figure 1. Monthly Sales Trend from 2009 to 2022

But after arranging and combining the monthly sales from 2009 to 2022, it was found that the fluctuation trend was relatively gentle compared to the annual data, as shown in Figure 2 for January sales data. Therefore, a monthly sales plan is formulated, and based on the annual sales forecast, exponential smoothing is used to predict monthly sales.

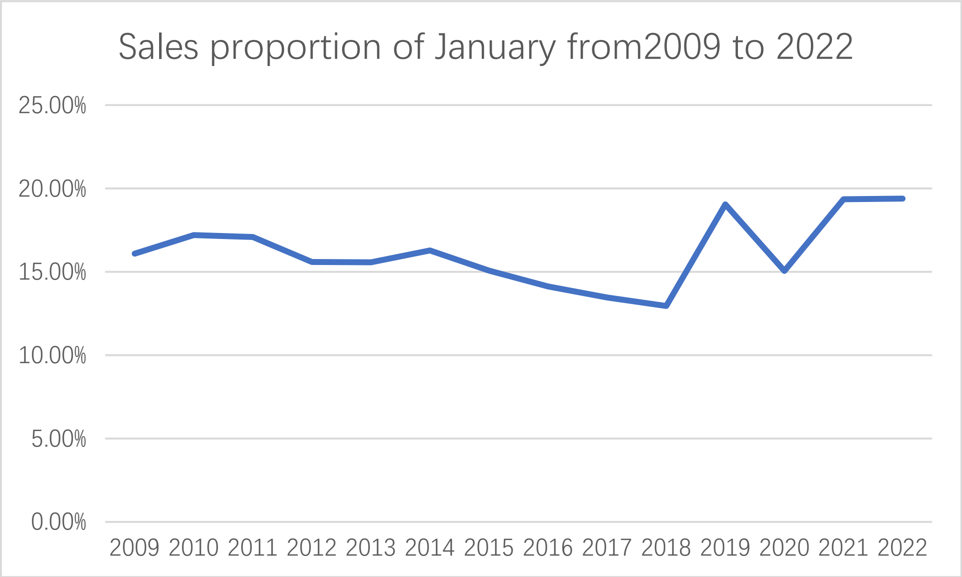

Figure 2. Sales Trend from 2009 to January 2022

4. Design of Monthly Sales Forecast Model

4.1 Smoothing Exponential Model

(1) Simple Smooth Model

Let Y_t be the observation data at time t, S_t be the smoothed data, and α be a real number between 0-1. The basic prediction formula is: $S_t = \alpha * Y_t + (1-\alpha) * S_{t-1}$. Among them, α is the smoothing coefficient, and the smaller the smoothing index value, the more suitable it is for time series data with more obvious fluctuations.Generally:

$S_t = \alpha * Y_t + \alpha(1-\alpha) * Y_{t-1} + \alpha(1-\alpha)^2 * Y_{t-2} + \cdots + \alpha(1-\alpha)^{t-2} * Y_2 + (1-\alpha)^{t-1} * Y_1$ ...... (Equation 1)

In the formula:

S_t—Predicted smoothing values for the t-th period;

Y_t- Actual value of period t;

α - Smoothing index.

From this, it can be seen that each smoothed data is obtained by weighting and summing past data. The closer it is to the current data, the greater its weight, and the greater its impact on the current period. Conversely, the earlier the data, the smaller its weight. The value of the smoothing coefficient is crucial in the smoothing index model, as its value determines the accuracy of the predicted value.

(2) Holt linear trend model

The Hote linear trend model is suitable for processing time series data with linear trend components but without seasonal components. Its prediction model is:

$$\begin{cases} T_t = \alpha * X_t + (1-\alpha) * (T_{t-1} + b_{t-1}) \\ b_t = \beta(T_t - T_{t-1}) + (1-\beta) * b_{t-1} \\ \hat{x}_{t+\tau} = T_t + b_{t\tau}, \tau = 1,2,\ldots, \end{cases} \text{...... (Equation 2)}$$

In the formula:

T - Current period;

τ - Predicting the number of preceding periods, also known as the prediction step size;

T_t- Estimate the trend of the t-th period using data from the previous t-period;

b_t- Estimate the trend increment b of the t-th period using data from the previous t-period;

x_t- Actual value of period t;

$\hat{x}_{t+\tau}$- Using the data from the previous tperiod, predict the value of the t+τ period;

α, β— Smoothing coefficient, with a value range of 0-1.

(3) Brownian linear trend

Brownian linear trend is suitable for processing time series data with linear trend components but without seasonal components.

$$\begin{cases} \grave{S}_t = \alpha X_t + (1-\alpha) \grave{S}_{t-1} \\ \ddot{S}_t = \alpha \grave{S}_t + (1-\alpha) \ddot{S}_{t-1} \end{cases} \text{...... (Equation 3)}$$

$$\begin{cases} a_t = 2\grave{S}_t - \ddot{S}_t \\ b_t = \frac{\alpha}{1-\alpha}(\grave{S}_t - \ddot{S}_t) \text{...... (Equation 4)} \\ F_{t+m} = a_t + b_t m \end{cases}$$

In the formula:

$\grave{S}_t$- One time exponential smoothing value;

$\ddot{S}_t$- Secondary exponential smoothing value;

m - Predict the number of ahead periods;

F_{t+m}- Actual value of the m-th period;

b_t - Estimate the trend increment b of the t-th period using data from the previous t-period;

α— Smoothing coefficient, with a value range of 0-1.

4.2 BIC Information Guidelines

The BIC information criterion is an asymptotic result that assumes that data, such as time series data, follows an exponential family distribution. By calculating the BIC value, the goodness of fit of the model is tested, and the value is used to select the optimal model. Generally, the smaller the BIC value, the better the explanatory power of multiple models.

$BIC \approx -2 * \ln(\mathrm{L}) + \mathrm{K}\ln(\mathrm{n})$...... (Equation 5)

In the formula:

L - Estimate the maximum value of the likelihood function of the model;

N - Number of observations;

K=The number of free parameters to be estimated.

4.3 Prediction Model Selection

The prediction results of different models are different, and which type of model is closest to the actual value can be judged by the square of the deviation between the actual value and the predicted value. The smaller the square of the deviation, the higher the prediction accuracy of the model. The one with the smallest square of the deviation is selected as the judgment model. In time series data, there are a series of data rather than a single data, so there is a sum of squares of deviations between multiple actual values and predicted values. If the size of each sum of squares is evaluated, for example, a simple model predicts that the sum of squares of deviations of a certain model is the smallest, but it is not the smallest in another group, resulting in different conclusions. Therefore, by measuring the minimum value of the sum of squares of deviations, it is regarded as the best prediction model.

Z=Min$\sum(X_i - X_{yi})^2{}_{\alpha j}$

X_i- Current actual value;

X_{yi}- Current forecast value;

αj- at the jth round, smooth the model with j=1,2,3. 1 represents a simple model, 2 represents a Hote linear trend model, and 3 represents a Brownian trend model.

5. Model application

5.1 Simple Model Prediction

Table 1. Simulation Fit Table

Fitting statistics	Average value	Standard error	Minimum value	Maximum value	Percentile 5	10	25	50	75	90	95
Stable R-squared	. 242		. 242	. 242	. 242	. 242	. 242	. 242	. 242	. 242	. 242
R square	-. 038		-. 038	-. 038	-. 038	-. 038	-. 038	-. 038	-. 038	-. 038	-. 038
RMSE	. 021		. 021	. 021	. 021	. 021	. 021	. 021	. 021	. 021	. 021
MAPE	8.681		8.681	8.681	8.681	8.681	8.681	8.681	8.681	8.681	8.681
MaxAPE	28.974		28.974	28.974	28.974	28.974	28.974	28.974	28.974	28.974	28.974
MAE	. 015		. 015	. 015	. 015	. 015	. 015	. 015	. 015	. 015	. 015
MaxAE	. 055		. 055	. 055	. 055	. 055	. 055	. 055	. 055	. 055	. 055
Normalized BIC	-7.519		-7.519	-7.519	-7.519	-7.519	-7.519	-7.519	-7.519	-7.519	-7.519

From the simulation fit table, the stationary R-squared value is 0.242>0, but R-squared value is -0.038, indicating that the fitting effect of the simple model is poor and cannot explain the trend of data changes well. Currently, the simple model is superior to the basic mean model. Normalized BIC=-7.519 has a certain explanatory power.

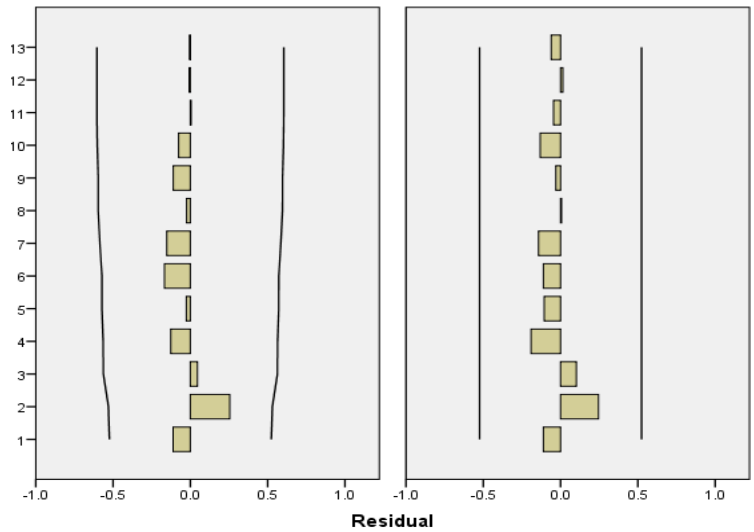

Figure 3. Residual ACF and PACF

From the residual ACF and partial autocorrelation PACF sequence diagrams, there is a clear tailing trend between ACF and PACF. From the ACF autocorrelation, after the 3rd order, there is a negative correlation between the observed values and the previous ones; From the partial autocorrelation of PACF, there is also a negative correlation between the current observation and the previous observation after the 3rd order.

5.2 Holt Linear Trend Model Prediction

Table 2. Simulation Fit Table

	averag	Standar	minimu	Maximu	Percentile						
Fitting statistics	e value	d error	m value	m value	five	ten	twenty-five	fifty	seventy-five	ninety	ninety-five
Stable R-squared	. 762		. 762	. 762	. 762	. 762	. 762	. 762	. 762	. 762	. 762
R square	. 740		-. 024	-. 024	-. 024	-. 024	-. 024	-. 024	-. 024	-. 024	-. 024
RMSE	. 022		. 022	. 022	. 022	. 022	. 022	. 022	. 022	. 022	. 022
MAPE	9.034		9.034	9.034	9.034	9.034	9.034	9.034	9.034	9.034	9.034
MaxAPE	27.939		27.939	27.939	27.939	27.939	27.939	27.939	27.939	27.939	27.939
MAE	. 015		. 015	. 015	. 015	. 015	. 015	. 015	. 015	. 015	. 015
MaxAE	. 053		. 053	. 053	. 053	. 053	. 053	. 053	. 053	. 053	. 053
Normalized BIC	-7.264		-7.264	-7.264	-7.264	-7.264	-7.264	-7.264	-7.264	-7.264	-7.264

From the simulation fit table, the stationary R-squared value is 0.762>0 and R-squared value is 0.74, indicating that the model fitting effect is applicable and can explain the trend of data changes. This indicates that the current simple model is superior to the basic mean model, with a normalized BIC of -7.264 and a certain degree of model explanatory power.

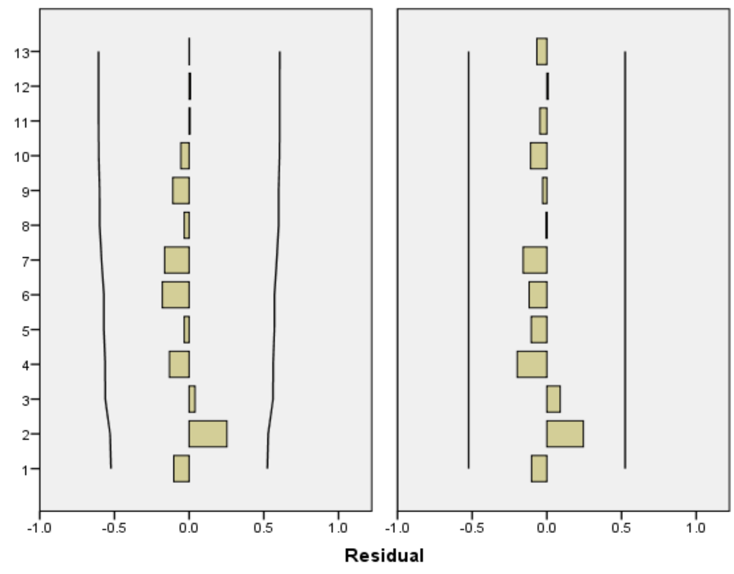

Figure 4. Residual ACF and PACF

From the residual ACF and partial autocorrelation PACF sequence diagrams, it can be seen that ACF has a clear truncation trend, while PACF has a clear tailing trend. From the ACF autocorrelation, after the 2nd order, the ACF value tends to approach 0; From the partial autocorrelation of PACF, there is a negative correlation between the current observation and the previous observation after the 3rd order.

5.3 Brownian Linear Model Prediction

Table 3. Simulation Fit Table

	average	Standard	minimum	Maximum	Percentile						
Fitting statistics	value	error	value	value	five	ten	twenty-five	fifty	seventy-five	ninety	ninety-five
Stable R-squared	. 742		. 742	. 742	. 742	. 742	. 742	. 742	. 742	. 742	. 742
R square	. 622		-. 122	-. 122	-. 122	-. 122	-. 122	-. 122	-. 122	-. 122	-. 122
RMSE	. 022		. 022	. 022	. 022	. 022	. 022	. 022	. 022	. 022	. 022
MAPE	8.348		8.348	8.348	8.348	8.348	8.348	8.348	8.348	8.348	8.348
MaxAPE	33.131		33.131	33.131	33.131	33.131	33.131	33.131	33.131	33.131	33.131
MAE	. 014		. 014	. 014	. 014	. 014	. 014	. 014	. 014	. 014	. 014
MaxAE	. 063		. 063	. 063	. 063	. 063	. 063	. 063	. 063	. 063	. 063
Normalized BIC	-7.441		-7.441	-7.441	-7.441	-7.441	-7.441	-7.441	-7.441	-7.441	-7.441

From the simulation fitting table, the stationary R-squared value is 0.242>0, and the R-squared value is 0.622, indicating that the fitting effect of the model is average and cannot explain the trend of data changes well. This indicates that the current simple model is superior to the basic mean model. Normalized BIC=7.441, with certain model explanatory power.

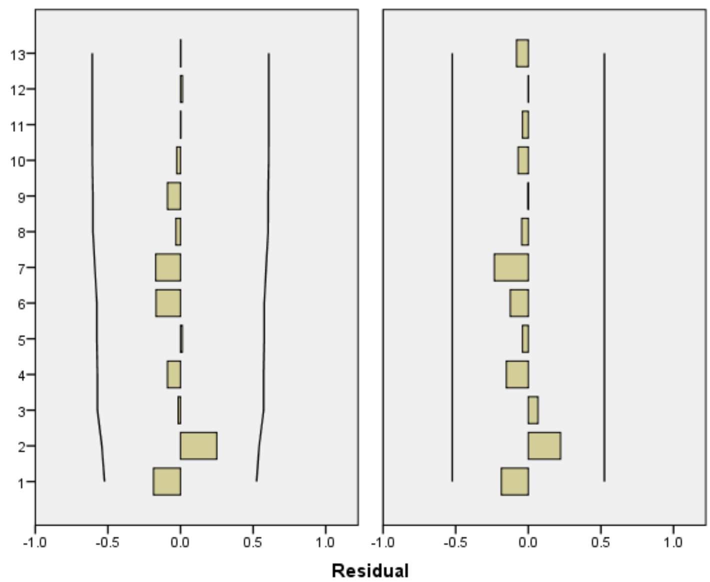

Figure 5. Residual ACF and PACF

From the residual ACF and partial autocorrelation PACF sequence diagrams, it can be seen that ACF has a clear truncation trend, while PACF has a clear tailing trend. From the ACF autocorrelation perspective, after the 2nd order, ACF approaches 0. From the partial autocorrelation of PACF, there is a negative correlation between the current observation and the previous observation after the 3rd order.

From the prediction results of the three smoothing models, it can be seen that the Holt prediction model is relatively more accurate. In order to further test the accuracy of the prediction results of the three models, the sum of squared comprehensive deviations is used to verify which model has a more accurate prediction result.

5.4 Comprehensive Deviation and Comparison of Prediction Results

By calculating the difference between the predicted and actual values of the three models, it was found that from 2009 to 2023, there was a significant difference between the predicted and observed values in 2012, 2016, 2017, and 2019, while in other years, the difference between the predicted and actual values of the three models was relatively small. From the calculation results of the sum of squares of the comprehensive deviations, it can be seen that the simple smooth comprehensive deviation sum of squares is 0.006, the Hote linear comprehensive deviation sum of squares is 0.0059, the Brown linear comprehensive deviation sum of squares is 0.0066, and the Hote linear comprehensive deviation sum of squares is the smallest, indicating that its prediction results are more accurate. Therefore, the Hote linear model can be selected as the January cigarette sales prediction model for L state.

Year	January Actual sales volume	Smooth prediction Simple smoothing	Hote linearity	Brownian linearity	Deviation and Simple smoothing	Hote linearity	Brownian linearity
2009	0.1609	0.1684	0.1674	0.1618	0.0001	0.0000	0.0000
2010	0.1720	0.1687	0.1691	0.1646	0.0000	0.0000	0.0001
2011	0.1709	0.1704	0.1714	0.1683	0.0000	0.0000	0.0000
2012	0.1559	0.1706	0.172	0.1696	0.0002	0.0003	0.0002
2013	0.1557	0.1631	0.1648	0.1609	0.0001	0.0001	0.0000
2014	0.1629	0.1593	0.1611	0.1562	0.0000	0.0000	0.0000
2015	0.1507	0.1612	0.1629	0.1585	0.0001	0.0001	0.0001
2016	0.1412	0.1558	0.1577	0.1523	0.0002	0.0003	0.0001
2017	0.1346	0.1484	0.1503	0.1433	0.0002	0.0002	0.0001
2018	0.1295	0.1413	0.1433	0.1346	0.0001	0.0002	0.0000
2019	0.1905	0.1353	0.1373	0.1274	0.0030	0.0028	0.0040
2020	0.1506	0.1635	0.1648	0.1627	0.0002	0.0002	0.0001
2021	0.1936	0.1569	0.1585	0.1568	0.0013	0.0012	0.0014
2022	0.1939	0.1756	0.1769	0.1806	0.0003	0.0003	0.0002
2023	0.1758	0.1849	0.1863	0.1933	0.0001	0.0001	0.0003
Sum of squared comprehensive deviations					0.0060	0.0059	0.0066

The accuracy of three prediction models was tested by predicting the sales volume of L state from 2009 to January 2023. Choose a more predictive and accurate model to predict sales in other months of L state, guide relevant departments of L state such as marketing, finance, and logistics to efficiently allocate resources according to market demand, optimize current configuration models and processes in each link, and achieve high-quality development of L state's tobacco industry.

6. Conclusion

This article takes the monthly sales of cigarettes in L region as the research object, collects data from 2009 to 2023 for a total of 15 years, studies the trend of monthly sales changes, and uses three smoothing models: simple smoothing, Hote linear, and Brownian linear to predict future monthly sales. The research process found that if there is a significant difference in sales data for the same month in different years, the difference method can be used to reduce its fluctuation trend and then make predictions, which can also achieve good prediction results. This monthly sales forecasting model has been validated for its feasibility in L state, and has significant reference value for predicting monthly sales in Sichuan and even other regions in China with similar operating environments as L region.

Fund Project

China Tobacco Corporation Sichuan Provincial Science and Technology Project "Research and Application of Cigarette Business Budget Management Based on Business Finance Integration" (SCYC202325)

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