International Journal of Economic Research

ISSN : 0972-9380

available at http: www.serialsjournal.com

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Volume 14 • Number 7 • 2017

Employing the Holt–Winters Model to Forecast and Assess the Efficiency of the Methods Used to Plan a Firm's Sales in the Upmarket Sector

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ABSTRACT

This paper provides a rationale for the need to reconsider the way businesses plan their sales in the upmarket sector and forecast and assess the efficiency of the methods they use to plan their sales. The authors make the case for the use of the Holt–Winters model to forecast product mixes in the upmarket sector. The current demand in the market for upscale clothing, footwear, and accessories is characterized by high volatility. There are multiple factors that may influence tangibly seasonal demand and retail companies' actual sales volumes. The haute couture industry normally operates in short 6-months-long seasons: the summer season (February–June) and the winter one (August–January). The shortness of these periods of sale of seasonal products makes it difficult to determine with a high degree of accuracy most of the trends in the dynamics of sales at the product level.

Keywords: Forecast models, Holt–Winters model, assessing the efficiency of sales planning methods, complex economic systems, upmarket sector

1. INTRODUCTION

The current demand in the market for upscale clothing, footwear, and accessories is characterized by high volatility. There are multiple factors that may tangibly influence seasonal demand and retail companies' actual sales volumes. The haute couture industry normally operates in short 6-months-long seasons: the summer season (February–June) and the winter one (August–January). One starts planning the procurement of seasonal merchandise 8-10 months prior to the actual start of the summer or winter sales season respectively, which induces an additional time uncertainty in calculating one's forecast models. The shortness of these periods of sale of seasonal products makes it difficult to determine with a high degree of accuracy most of the trends in the dynamics of sales at the product level. The large number of unique products and a lack of relevant historical data on sales on many of these articles make it hard to correctly forecast the average pace of sales at the level of a specific product. Every season, one witnesses both substantial changes in demand among brands and shifts in the overall structure of demand among price segments on a breakdown by type of product.

Constructing as accurate forecasts of the structure of demand and sales volume as possible for future seasons is the more important analytical objective in the retail of the high-price segment for clothing, footwear, and accessories (Ong, Choy & Cheong 2013).

Ceteris paribus, obtaining highly accurate sales forecasts enables companies to outperform their competition by attaining maximally accessible levels of gross profit. In optimizing a company's non-commodity expenditure, forecasts of future operating costs are put together with great accuracy and, in a way, are an inherently known constant for several periods into the future. It follows that by maximizing its gross profit a company actually maximizes its end net profit. The principal goal of any commercial retail company is to generate profit through constant growth in sales by way of physical expansion and/or technological development, and the ability to achieve this goal largely depends on the accuracy of forecast models that determine the volume and structure of client demand.

To forecast sales in the fashion industry, businesses employ the various statistical methods, like the moving average method, the weighted moving average method, linear regression, the first, second, and third order exponential smoothing models (Liu, et. al. 2013), and Bayesian methods. Wide use has been made of methods of time series analysis (*MachineLearning, n.d.*), like ARIMA and SARIMA (Penn State University's Eberly College of Science, n.d.). The advantages of using all the above methods include fluent application in practice and simple result interpretation. The main weakness of these methods is that the accuracy of forecasts generated via them is relatively not very high under conditions of much uncertainty about the behavior of factors governing the volume of client demand within the industry. More accurate and complex forecasting methods to apply are methods of panel analysis (including their hybrid variants), artificial neural network modeling, and mathematical modeling using fuzzy logic (Frank, et. al. 2002). In most cases, the accuracy of these models surpasses that of traditional statistical methods. However, an obstacle to implementing these methods is their technical complexity, which requires engaging considerable company resources (Kaya, et. al. 2014). Also it is hard to interpret the result in presenting data within the framework of the system of decision support and making for individuals making the actual investment decisions. There is a lack of well-worked criteria allowing one to illustrate, by way of factor decomposition, the clear-cut logic and forecasting advantage of new hybrid and network methods (Danko, et. al 2016).

Virtually all major sections of planning activity for future seasons, including procurement budgeting, sales plans for sales personnel, putting together key efficiency indicators for heads of line units and management, financial planning, and others, are in direct dependence on the quality of demand assessment. An especially complex process is making sales forecasts for new retail facilities that are still in their development stage and do not possess relevant statistics. In the initial stage of the active formation of a client base, sales statistics for a new facility are not representative in many respects. Thus, it pays to look separately at retail facilities that are characterized by a sustainable growth trajectory and an extensive client base and those that are in the stage of initial growth and development and have a less loyal client base for now. A major stage in this study will be verifying the authors' hypothesis about the need to shift from the basic trend method of forecasting sales for brands forecasted at a high level of aggregation (brands and product categories) to the more complex methods.

These integrated methods include the Holt–Winters smoothing method, panel analysis, and neural networks (Recurrent neural network, n.d.). The major criteria for choosing this model include the technical possibility of assessing changes in the accuracy of forecasts, integrating the method into the company's information systems, and formulating the logic of forecasts within the framework of the existing system of decision support and making at the company. Indeed, it appears worthwhile to fine-tune one's actual assessments of changes in the accuracy of one's forecasts based on historical data, as well as ascertain the technical possibility of integrating the method into the company's information systems and formulating the logic of forecasts in a set of existing factors for individuals who make decisions.

Just like many other sectors of the economy, the fashion industry (clothing, footwear, and accessories) is quite a competitive sector. Competing for the consumer, companies devise complex methods and systems for interacting with the client. To achieve boosts in the caliber of their mid-term planning (timeframes of a month to a year), companies invest heavily in the development of forecast models (TsUM, n.d.; Deloitte, 2015; Schindler 2016). The market for haute couture is subject to general fluctuations in the economy's consumer demand. The sector behaves procyclically (people tend to stop buying clothing, footwear, and accessories during a recession and go on a shopping spree for these products when the economy is booming). Among the sector's specific factors are pronounced seasonality, associated with weather indicators varying from the average figures, continually updated product mixes (changes in texture, color, etc. – the fashion trends factor), a lack of long-standing historical statistics at the level of a specific article. A solution companies may have for these information limitations are complex hierarchical forecasting systems and really simple models alike.

Scholar S. Thomassey has identified 3 groups of merchandise based on the lifetime of a specific product (the number of seasons in which a certain article is manufactured and supplied to the market, to an accuracy of color , texture, and size) (Carlos 2016; Thomassey 2010). Basic products are supplied and sold throughout the year. This group includes, for instance, men's classic dress shirts, underwear, jeans, and wear-at-home clothing (in international supplier documentation, this type of merchandise may be termed 'carry-over list', 'permanent collection', or 'base collection').

Seasonal merchandise (trendy merchanidse) is sold during one season and, normally, is not manufactured again.

A bestseller product is one that sells successfully in a season and is then much sought after among consumers in subsequent seasons (*i.e.*, it is not tied to a short-term fashion trend). This type of merchandise is, normally, put back into manufacture and sold in subsequent seasons with minor changes being made in its design (there may be boosts in color and size supply) (Thomassey 2014).

2. METHODS

Depending on the type of product, it pays to use different methods of sales planning and forecasting. With bestseller and basic merchandise, there is always access to the more extensive statistics at the level of a specific product. While when there is seasonality, one may want to use the Holt–Winters multiplicative model (multiplicative seasonality and a trend) and Holt-Winters additive model (additive seasonality and a trend).

The Holt–Winters model factors in both seasonal fluctuations and sales upturn/decline trends (in particular, when the product itself appears on the market for the first time or, conversely, when there appears one that is a competitor to that product):

$$\hat{x}(t+d) = (L_t + d_S * T_t) * S_{t+(dmods)-s}, \quad (1.1.6)$$

$$L_t = \alpha_1 * (x_t / S_{t-s}) + (1-\alpha_1) * (L_{t-1} + T_{t-1}), \quad (1.1.7)$$

$$T_t = \alpha_2 * (L_t - L_{t-1}) + (1-\alpha_2) * T_{t-1}, \quad (1.1.8)$$

$$S_t = \alpha_3 * (x_t / L_t) + (1-\alpha_3) * S_{t-s}, \quad (1.1.9)$$

$$\alpha_1, \alpha_2, \alpha_3 \quad (0,1)$$

where T_t = Parameter for the trend,

L_t = Parameter for the forecast cleared from the trend and seasonality,

$S_i, i \in 0,\ldots, s-1$ = Seasonal profile,

and d = Forecast horizon.

The Holt model additively factors in seasonality and, just like the previous model, the trend:

$$\hat{x}(t+d) = L_t + d * T_t * S_{t+(d \bmod s)-s}, \quad (1.1.10)$$

$$L_t = \alpha_1 * (x_t - S_{t-s}) + (1-\alpha_1) * (L_{t-1}) + T_{t-1}, \quad (1.1.11)$$

$$T_t = \alpha_2 * (L_t - L_{t-1}) + (1-\alpha_2)T_{t-1}, \quad (1.1.12)$$

$$S_t = \alpha_3 * (x_t - L_t) + (1-\alpha_3) * S_{t-s}, \quad (1.1.13)$$

$$\alpha_1, \alpha_2, \alpha_3 \quad (0,1)$$

where T_t = Parameter for the trend,

L_t = Parameter for the forecast cleared from the trend and seasonality,

$S_i, i \in 0,\ldots, s-1$ = Seasonal profile,

d = Forecast horizon.

All the parameters α in the exponential smoothing models are tuned experimentally (by way of numerical methods).

Based on standard models, in practical situations it is a common practice to build hybrid models demonstrating greater forecasting accuracy (accuracy is determined relative to statistical criteria chosen).

Thus, by its structure the set of data under examination correlates tangibly with sales in the fashion industry. As their criterion for comparing the models the authors employ the RMSE (root-mean-square error) and MAE (mean absolute error).

Assume that $X = \{x_1, \ldots, x_T\}$ is your time series (monthly sales results), T_t is your adjusted (smoothed) annual sales, and S_t is your monthly sales set apart from the annual values. The authors employ the following modification of the exponential smoothing method:

$$T_t = \alpha * \sum_{i=0}^{11} X_{t-1} + (1-\alpha) * T_{t-1}, \quad (1.1.14)$$

$$S_t = (\gamma * X_t) / \sum_{i=0}^{11} X_{t-1} + (1-\gamma) * S_{t-12}, \quad (1.1.15)$$

where α and γ = smoothing parameters. Forecasts are put together in the following way:

$$\hat{x}_t(k) = T_t * S_{t+k-12}, \text{ for integers } k = [1,12], \quad (1.1.16)$$

$$\hat{x}_t(k) = T_t * S_{t+k-24}, \text{ for integers } k = [13,8], \quad (1.1.17)$$

This method may be regarded as a sort of hybrid of the Holt–Winters model and the moving-average one.

The actual application of these forecasting methods will be examined through the example of TsUM, one of Russia's most renowned high-end department stores located in Moscow, based on the type of merchandise. In terms of merchandise within the four-seasons (basic) and bestseller categories, the company has a deeply organized forecasting system that is based on the pace of sales (inventory turnover) and statistical distribution of sales for a specific category across the months (factoring in the connection between such factors as a month within the season, temperature, a pre-holiday period, and the public's actual need for a certain category of merchandise). Forecasts for seasonal merchandise, especially for brands with relatively minor procurement volumes (*e.g.*, a few tens of thousands of euros worth of merchandise), are put together by way of the basic trend method, which inputs increase into a forecast of sales through to the end of the season based on the actual rate of increase. Thus, a forecast of sales in purchase prices through to the end of the season will look as follows:

$$\text{SalesCost}_{\text{season},\, t} = \text{SalesCost}_{\text{std},\, t} + \frac{\text{SalesCost}_{\text{std},\, t}}{\text{SalesCost}_{\text{std},\, t-1}} * \text{SalesCost}_{\text{std}-bs,\, t-1} \tag{2.6.1}$$

where $\text{SalesCost}_{\text{season},\, t}$ = sales through to the clearance sale period in the current season, $\text{SalesCost}_{\text{std},\, t}$ = sales as of currently in the season, $\text{SalesCost}_{\text{std},\, t}/\text{SalesCost}_{\text{std},\, t-1}$ = ratio of sales as of currently in the season to sales in the same period of the previous season (compared are a winter season and its winter counterpart or a summer season and its summer counterpart), $\text{SalesCost}_{\text{std}-bs,\, t-1}$ = sales in the previous season from the current date through to the moment the clearance sale period begins.

Among the method's major strengths are its ease of use and, most of the time, its ability to correctly keep track of brand growth/decline trends. In terms of efficiency, this method may be compared to the Holt–Winters additive and multiplicative models. Here, it is worth establishing the naïve forecasting model as the basic model for comparison. This model uses the last period's actuals as this period's forecast, *i.e.* employs the approach "the best forecast for tomorrow is today's value". A promising area for the development of the forecasting system in a company may be organizing specific neural networks adapted under the business and integrating them into the company's IT systems. Due to the complexity of grouping, setting up, and testing data for neural networks, the authors suggest assessing the potential efficiency of this method in an indirect manner for now. Based on an investment-related assessment of costs for a project on building a neural network for forecasting sales in terms of the payroll budget for a project team that is going to engage in implementation activity in the project's active stage and then guide the project, doing all the setting up and enhancing work required, it will be possible to determine the project's pay-off period and parameters. In particular, it pays to determine the procurement volume, which is also part of forecasting under this model, the percentage of improvement in forecasting using the neural network, and the increase in profit on the given volume of merchandise with different parameters of profitability being used.

As is evidenced in Table 7.1, the Holt–Winters methods are the most promising in terms of replacing the basic trend method. These methods can be easily integrated into the IT systems (OLAP, Axapta, internal software), the models providing for the isolation of plain decomposition components: level, trend, and seasonality, while implementing the method in corporate culture will require moderate efforts thanks to its moderate complexity.

Table 7.1
Strengths and Weaknesses of the Various Trend Forecasting Methods

	Method	*Implementing * in IT*		*Implementing in corporate culture*		*Possibility of detailing*	
	Current – trend analysis	**Implemented in all IT systems**	+	**Methodology and terminology are in wide use in the company**	+	**Fact, trend**	+
1.	**(Holt-Winters)**	**Possibility of implementation in IT systems**	+	**Possibility of using the methodology and terminology at all levels in the company**	+	**Trend, seasonality, level**	+
2.	Panel analysis (Panel data)	Hard to implement and manage in IT	–	Possibility of using the methodology and terminology at all levels in the company	+	Weights of independent factors (depends on the model's complexity)	+
3.	Neural networks	Hard to implement and manage in IT	–	Hard to use for all interested parties	–	There is no factor interpretation	–

3. RESULTS

Table 7.1 illustrates the performance of models for forecasting using the basic method and the Holt–Winters methods. The comparison is performed based on U-statistics (comparison with the naïve forecast, whereby the last period's actuals are used as this period's). Thus, if the U-statistics value exceeds 100%, the method's accuracy is not very high and in that case it pays to utilize the plain "naïve" forecast, focusing on the last full known month as the best approximation of the future. The lower the U-statistics value, the greater the accuracy of the method under examination.

Table 7.2
Performance of Models for Forecasting Using the Traditional Method and the Holt-Winters Methods
*** – U-Statistics**

Quantity of statistics	*Retail facility*	*Type of product*	*Current Trend analysis*	*Holt-Winters (Mult.)*	*Holt-Winters (Addit.)*
4 seasons	All	All	88%*	73%	68%
4 seasons	TsUM	All	83%	78%	66%
4 seasons	DLT	All	174%	127%	104%
4 seasons	TsUM	Clothing	82%	73%	65%
4 seasons	DLT	Clothing	169%	124%	105%
4 seasons	TsUM	Footwear	91%	71%	64%
4 seasons	DLT	Footwear	203%	151%	97%
3 seasons	All	All	85%	71%	65%
3 seasons	TsUM	All	78%	65%	63%

Quantity of statistics	*Retail facility*	*Type of product*	*Current Trend analysis*	*Holt-Winters (Mult.)*	*Holt-Winters (Addit.)*
3 seasons	DLT	All	265%	153%	151%
3 seasons	TsUM	Clothing	76%	63%	61%
3 seasons	DLT	Clothing	257%	156%	151%
3 seasons	TsUM	Footwear	93%	58%	56%
3 seasons	DLT	Footwear	328%	125%	119%

As is evidenced in the first row of Table 7.2, which covers all the 4 seasons, all the retail facilities, and all the product categories, the current and trend methods exhibit greater accuracy than the more simplified basic method of naïve forecasting, with the Holt–Winters models demonstrating greater accuracy on the U-statistics criterion than the method of plain trend approximation. Next, when it comes to specific retail facilities, namely TsUM and DLT (Saint-Petersburg's largest department store), the methods exhibit greater accuracy for TsUM, with U-statistics values of over 100% demonstrated for DLT. These values for DLT substantiate the authors' hypothesis, whereby prior statistics are relatively unrepresentative for most actively developing new retail facilities and it is not worth making forecasts for future periods based on those statistics.

Examined below are better detailed forecasts across the categories. The use of some of the models with respect to clothing and footwear is characterized by greater accuracy both for TsUM and for DLT, with coefficient values for DLT staying at the level of and lower than those obtained by way of naïve forecasting. Based on these comparisons at the categories level, it, likewise, is possible to infer for TsUM that the Holt–Winters models exhibit greater accuracy than trend analysis. When it comes to a model that selects optimum coefficients among the smoothing models, greater accuracy over 3 seasons is observed for TsUM with the trend model and the Holt–Winters models. Accuracy for DLT over 3 seasons is down.

4. DISCUSSION

In discussing the above comparisons of the Holt–Winters methods and the basic trend method, the authors suggest considering the following points.

The complexification of the methods results in greater forecast accuracy (D'Arpizio, et. al. 2015). When it comes to forecasting sales at TsUM at a high level of aggregation, the Holt–Winters additive model performs better than the multiplicative version and the current trend model. It pays to select model coefficients separately for footwear and clothing brands. For DLT, which is going through an active phase of growth, the use of historical data for forecasts may lead to considerable deviations of the plan from the fact. Thus, at the current stage of its development DLT may be better off using the naïve forecasting method, *i.e.* the "the best forecast for tomorrow is today's value" approach. Based on this principle, it pays to focus on the "today" base, which may be represented by the last month, 2 months, etc. (Kitova, et. al. 2016; Danko, et. al. 2016a). It also follows from the results obtained that it appears to be promising and advisable to employ integrated network forecasting models for the TsUM retail facility.

The Holt–Winters model (its additive variant) exhibited 5.7% less deviation in sales forecasts for 2 months relative to the absolute values of actual sales in purchase prices. Thus, for a 5-month sales period there will be an improvement of about 2.3% in the accuracy of the volume of sales in purchase prices. Table 3 illustrates potential increases in the company's profit if the Holt–Winters model is used, depending on the business's order volume and net margin (net sales margin).

Table 7.3
Losses of Net Profit in Thousands of Euros Depending on the Business's Net Margin and Order Volume (in a Season)

	Net return on sales					
Worth of procurement, million euros	**5%**	**10%**	**15%**	**20%**	**25%**	**30%**
1	2	4	6	8	10	12
2	4	8	12	16	20	24
5	10	20	29	39	49	59
10	20	39	**59**	79	98	120
20	39	79	120	155	195	235
50	98	195	295	395	490	590

One's missed receipts are established through the determination of standard target receipts based on every thousand euro order. One inputs the following possible parameters of target sales: 60% of the merchandise at full prices through to the clearance sale period and 15% of the merchandise during the clearance sale period, with an average discount of 40%. There is a mark-up of 150% over the factory price. Costs associated with shipping, customs processing, and VAT come to about 25% of the purchase price at the factory. Then the markup over the full price, inclusive of shipping and processing, will total 100%. Thus, for every thousand euros (the euro taken as the main currency herein) one derives target receipts in the amount of 1,725 euros. If things are budgeted inaccurately, the procurement budget will be 2.3% smaller, which will – ceteris paribus – lead to comparable losses in sales, *i.e.* for a 1,000 euro order there will be a loss in the amount of about 40 euros. As an example, with a 15% net margin 40 euros worth of missed receipts would mean a loss of 6 euros in net profit. So if it is millions of euros worth of ordered merchandise, a loss of 2.3% in receipts leads to tens of thousands of euros not being made as one's profit. Thus, if the simplified forecasting method is employed, a company with a 10 million euro procurement budget for a season and a 15% net return on sales will sustain a loss of 60,000 euros in net profit in that season (a half-year).

5. CONCLUSION

Thus, it may be stated that with respect to the market under examination the Holt–Winters model is a classic forecasting model that is easy to implement. A set of standard and hybrid exponential smoothing models may soon enter wide use as an effective instrumentarium in the real sector of economy. Right now, many leading companies specializing in the development of business applications are incorporating these methods into their planning modules as fundamental components. This set of models makes it possible to swiftly generate a necessary forecast and quite plainly explain the logic behind the method and result to individuals responsible for making key decisions at the company. Under a certain balance of companies' interests between a forecast's accuracy and its ease of use and implementation, exponential smoothing may well be adopted as their primary method of planning.

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