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IMPACT OF GOVERNMENT POLICIES ON FASHION INDUSTRY PROFIT GENERATION USING EXPONENTIAL SMOOTHING MODELS

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Abstract: In Colombia, the fashion industry faces growth challenges due to annual volatility, causing the need for proactive policies based on profit forecasts to manage the economic, social and political repercussions. This study employs three exponential smoothing methods, including Single Exponential Smoothing "SES", Double Exponential Smoothing "DES", and Holt Exponential Smoothing "HES", to determine the most accurate operating profit forecasting model. The DES and HES models, with specific smoothing parameters, consistently outperform the others, showing low values of mean absolute percentage error "MAPE", "MAD" and "MSD", indicating their competence in profit prediction. Consequently, these models become crucial tools to evaluate the effectiveness of government policies and establish benchmarks to describe and predict profits and financial margins in the Colombian fashion and clothing industry.
Keywords: Time series, smoothing models, financial process modeling, decision making, quantitative methods in finance, EBITDA, government policies, fashion industry analysis

INTRODUCTION

The impact of Industry 4.0's technological tools has sparked a revolution in the analysis and characterization of various industries. By harnessing platforms that tap into shared data, these tools have empowered both public and private industry entities to craft policies and make decisions with enhanced reliability. They utilize models and algorithms that aid in comprehending the performance patterns exhibited by companies within a given industry, ultimately facilitating the exploration of optimization alternatives (Crnjac, Veža, & Banduka, 2017; Pereira & Romero, 2017; Andieva & Ivanov, 2019; Ivanov, Luk'yanova, & Belova, 2020; Ahmad, Miskon, Alabdan, & Tlili, 2020). In today's dynamic and intricate market landscape, turbulence reigns and casts a shadow of uncertainty over traditional manufacturing industries such as fashion and apparel. These industries are forced to take proactive measures to improve the financial performance of their businesses as a survival imperative (Jiang, 2020). Countries such as Colombia must develop policies based on statistical models that elucidate the financial performance of their industries. The aim of these models is to uncover relevant patterns that can be juxtaposed with policies and decisions made by governments at different points in time. This comparative analysis is crucial to understand and describe the industry's response to policy changes and to understand their impact (Chlomou & Demirakos, 2020; Ozturk & Karabulut, 2020; Tamuleviˇcien˙e & Androniceanu, 2020).

To achieve this goal, it is important to develop studies that predict future economic trends by analysing annual data records. These studies will enable the establishment of the success of companies in the future and how government policies, supported by financial indicators, will focus on making industries more dynamic (Chlomou & Demirakos, 2020; Ozturk & Karabulut, 2020; Tamuleviciené & Androniceanu, 2020).

Nevertheless, it is crucial to recognise that projection models have inherent limitations, stemming from factors such as a limited set of observations, reliance on conventional methodologies and the shortness of the available time series data (Schueler, 2020; Bouwens, De Kok, & Verriest, 2019; Rozenbaum, 2019; Vidal-Garcia & Ribal, 2019; Kany, 2016).

This paper presents a comparative analysis of several supervised forecasting models, including simple moving average, simple exponential smoothing, second-order exponential smoothing and Holt exponential smoothing. The models are evaluated using

EBITDA, a financial indicator widely used by academia and the stock market industry to assess a company's real earnings, determining a company's gross operating profit before accounting for its financial expenses, which support corporate mergers and acquisitions. (Anusha & Umasankar, 2020, Vol.11; Schüle, Bungeroth, Kemper, Günnemann, & Neumann, 2019; Hsieh, Giloni, & Hurvich, 2020; Carpio, Juan, & López, 2014).

This study explores the use of exponential smoothing models to analyse the EBITDA ratio and EBITDA margin of the fashion industry. The financial data used in this study spans from 1995 to 2019 and was reported by companies in the sector to the authorities.

The results show that Holt Exponential Smoothing (HES), followed by Double Exponential Smoothing (DES), perform better than the other models used in the analysis of EBITDA and EBITDA margin behaviour patterns in the Colombian fashion industry.

MATERIALS AND METHODS

TECHNICAL SPECIFICATIONS

In the course of this project, we constructed a database using data sourced from the Colombian Superintendence of Corporations (SIS), spanning the period from 1995 to 2019, representing the most extensive timeframe available in SIS reports. Our analysis was confined to data exclusively from the garment industry.

The data, originally in Excel format, was subsequently imported into a PostgreSQL database. The development of the application was executed on a computer boasting 16GB of RAM, an 8th Gen. Intel Core i7 Processor, and a GeForce GTX 1070 With Max-Q Design, featuring 8GB GDDR5. The operating system in use was the x64 bit version of Microsoft Windows 10.

The methodology was implemented using the Python 3.11 programming language, with the PostgreSQL library employed for database management.

Financial performance data are taken from the annual financial statements submitted by Colombian companies to the SIS. Discrepancies have been detected in the financial data contained in the Excel files used to record and archive these financial statements. These parameters, which measure the performance of each industry, have a significant influence on the formulation of national economic development policies.

This influence can impose constraints on feasible achievements, which underlines the imperative need to examine industrial behaviour and variations in order to check their effectiveness.

To ensure the accuracy of forecast data, we normalise financial data for operating profit, depreciation and deferred items, also taking into consideration, inflation rates for each year. This normalisation process is executed within a Python data cleansing framework, using robust and well-established tools and methodologies **Python** and **PostgreSQL**, based on the structure shows in Figure 1. The data cleansing framework comprises multiple layers, each assigned a specific task related to data management, storage, and queries for index calculation. Within the context of the **EBITDA** model, the computation of operating profit, depreciation, and amortisation is necessary, with each of these variables corresponding to a column in the CSV files. The primary challenge lies in the fact that the name of each column changes annually. Therefore, the initial layer, which focuses on standardisation and data organisation, plays a pivotal role in this model.

PREDICTIVE ANALYTICS

As illustrated in Figure 2, the EBITDA index exhibits pronounced fluctuations that can impact the subsequent data analysis. To mitigate these fluctuations, a moving average filter was employed. However, as depicted in Figure 3, this approach introduces an approximation error. High-order exponential smoothing, serving as an extension of moving averages by employing geometrically decreasing weights, enhances the precision of the approximation to actual data. Hence, it is the chosen method in this study.

To examine the behaviour of companies in the fashion industry in Colombia, a predictive model was developed using time series analysis. This model uses historical financial data to calculate EBITDA (earnings before interest, taxes, depreciation and amortisation).

As highlighted, EBITDA serves as a financial metric used by various methods to assess the value of a company. It is also used by investors and analysts to assess operating profitability and to facilitate comparisons between companies in the same industry. Complementing EBITDA is EBITDA margin, which helps determine the level of efficiency in profit generation. Robust EBITDA and a robust EBITDA margin can signify a well-run and profitable company. In addition, lenders and creditors use EBITDA and EBITDA margin to gauge a company's ability to meet its debt obligations, as EBITDA reflects the company's ability to generate cash and meet interest payments on its debt.

Given its ability to reflect a company's real profits, this study has chosen to use EBITDA, together with EBITDA margin, to analyse real profit trends in the fashion industry in Colombia.

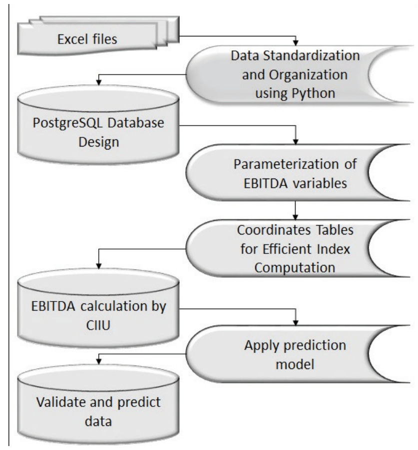

Figure 1. Flow chart used for data collection, SQL queries and development of the predictive analytics model based on the EBITDA index. Author's work

METHODS AND RESULTS

In order to make forecasting analysis Exponential Smoothing and Moving Average models were used (Chow, 1965).

EBITDA is calculated based on the information contained in the official report of a company's financial statements, including the balance sheet, income statement, and cash flow statement, which are submitted to the Superintendence of Companies (SIS) for financial reporting.

$$EBITDA = Revenue - Operating\ Expenses + Depreciation + Amortization$$
$$EBITDA = OperatingProfit + Depreciation\ Expense + Amortization\ Expense$$

(2)

The financial statements were stored as tables in the PostgreSQL database, along with their corresponding deflated values, in conjunction with their respective coordinate tables, to expedite the computation of the ratios. The EBITDA index computation was executed utilizing the commands SUM BY CLAUSE and WHERE LIKE. In order to minimize CPU processing time, coordinate tables containing information about the location of operating profit, as well as amortisation and depreciation expenses, were employed. Furthermore, the EBITDA margin was calculated to analyse the profitability of the fashion industry in Colombia in terms of operational processes. All of these indices were computed using automated algorithms in Python and PostgreSQL.

Figure 2 illustrates the growth in gross profit of companies in the industry, starting with at EBITDA of 120 million Colombian pesos (approximately 121,501 US) in 1995, and reaching its zenith in 2013 with at EBITDA of 2.5 billion pesos (approximately 1,297,470 US).

The second trend shows a decrease in the EBITDA in 2014, amounting to 1.6 billion pesos (approximately USD 668,770). This downward trend continues until 2019, when the industry's EBITDA amounts to 1.0 billion pesos (approximately USD 305,144). Despite small fluctuations in both trends, they have a negligible impact on the pattern of behaviour of each trend.

It must be noted that the increase observed in the first trend and the decrease in the second trend within the fashion industry between 1995 and 2019 might lead to an incorrect conclusion regarding the historical profit loss of the industry. This could imply that the companies comprising the industry were sacrificing a portion of their profits to sustain their operations. For this reason, the research also considered the behaviour of the EBITDA margin, which represents the relationship between EBITDA and Total Revenue (Bouwens, De Kok, & Verriest, 2019; Rozenbaum, 2019; Vidal-Garcia & Ribal, 2019). This index makes it possible to compare the operating profit obtained by the companies in the industry with the total sales figures recorded in each year of analysis.

As can be seen, the trend of the percentage profit margin shows a consistent pattern. It starts in 1995 with a margin of 5% EBITDA margin, rises to 11.9% in 2015 and finally settles at a margin of 9.6% EBITDA margin in 2019. In essence, the fashion industry has experienced growth in its gross profit margin since 1995. It must be noted that this growth has been steady rather than exponential, maintaining an average of 9.2% in EBITDA margin from 1995 to 2019.

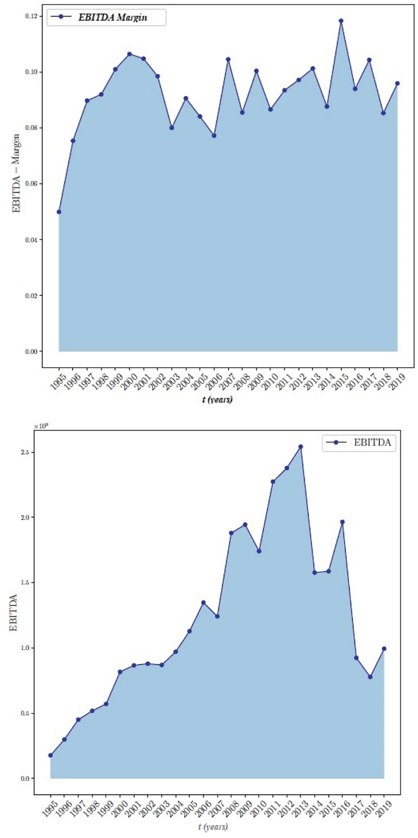

Figure 2. EBITDA/EBITDA Margin for Fashion industry in Colombia

SIMPLE MOVING AVERAGE

In the field of financial studies, it is common to carry out time series smoothing procedures to discern different patterns. Among the various data smoothing techniques, this paper will use the simple moving average, which is the most widely used method in financial forecasting. A simple moving average "SMA" (Hsu, Hsu, Zhou, & Ziedonis, 2019; Chantarakasemchit, Nuchitprasitchai, & Nilsiam, 2020; Milunovich, 2020) of span *N* weights all equals to *1/N* for the most recent *N* observations , and zero for the others. Let MT be the moving average, then the *N*-span moving average at time period T is

$$M_T = \frac{Y_{T-1}+Y_{T-2}+\cdots+Y_{T-N+1}}{N} = \frac{1}{N}\sum_{t=T-N+1}^{T} Yt \tag{2}$$

Let σ^2 be the variance of an individual observation and assuming that the observations are uncorrelated then the SMA variance is

$$Var(M_T) = \mathrm{Var}\left(\frac{1}{N}\sum_{t=T-N+1}^{T} Yt\right) = \frac{1}{N^2}\sum_{t=T-N+1}^{T} Yt\ \mathrm{Var}\left(\mathrm{Yt}\right) = \frac{\sigma^2}{N} \tag{3}$$

As can be seen, SMA variance depends of the time period use for its calculation. For large values of N, Var (MT) tends to 0 and for very small values it tends to ∞, common moving average lengths are 5, 10, 20, 50, 100, 200. The longer the time frame for the moving average, the smoother the simple moving average. A shorter-term moving average is more volatile, but its reading is closer to the source data, as can be observed in Figure 3.

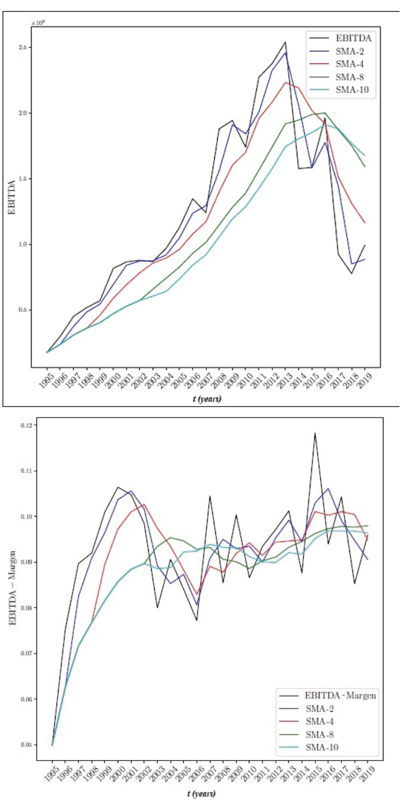

Figure 3. Moving Average EBITDA/EBITDA-Margin for Fashion industry in Colombia

SIMPLE EXPONENTIAL SMOOTHING

Simple Exponential Smoothing can provide different smoother for the EBITDA index based on α selection in the model where $\alpha \in [0, 1]$ (Montgomery, Jennings, & Kulahci, 2015). The model can be represented as

$$Yt = f\,(t,\beta) + \varepsilon t \ (4) \tag{4}$$

where β is the vector of unknown parameters, εt represents the uncorrelated errors which has zero mean value a constant variance. SES is a member of this general class of models, obtained by considering the constant process $Y_t = \beta_0 + \varepsilon_t$. To find least squares estimate for β_0, a geometric power series with decreasing weights in time we called SSE is minimized by taking its derivative with respect to β_0 and considering $|\theta| < 1$

$$SS_E = \sum_{t=0}^{T-1} \theta t\left(y_{T-t} - \beta_0\right)^2 \underset{\partial\beta 0=0}{\Rightarrow} y_T$$

$$= \hat{\ }\beta_0 := \frac{1-\theta}{1-\theta_T}\sum_{t=0}^{T-1}\theta tYT - t \underset{T\to\infty}{\rightarrow} \sum_{t=0}^{T-1}\theta tyT - t \tag{5}$$

SES can be written in a recursive form as ȳT = (1 − θ) ȳT + θȳT 1 = λȳT + (1 − λ) ȳT−1. Calculating in a recursive way starting with ȳ 1, ȳT can be written as:

$$\bar{y}_T = \lambda\sum_{t=0}^{T-1}(1-\lambda)^t\, Y_{T-t} + (1-\lambda)^T\,\bar{y}_0 \tag{6}$$

It must be noted that $(1-\lambda)\,T \underset{T\to\infty}{\longrightarrow} 0$, therefore contribution of $\bar{y}_0$ to $\bar{y}_T$ is almost null. However, in this work the frequently initial data ˜ $Y_0 = Y_1$ is used or the mean value estimator $\bar{y}_0$ = Y when the time series is constant at the beginning. Under the independence and constant variance assumptions, using variance properties, it can be shown that $Var(\bar{y}_T) = \lambda Var(\bar{y}_T)/(2-\lambda)$, as can be seen for $\lambda = 1$ an unsmoothed version of the time series is obtained, based on forecasting errors and confidence intervals the right λ can be chosen (Chow, 1965; Montgomery, Jennings,

& Kulahci, 2015; Ledolter & Abraham, 1984; Cogger, 1974)

In this work, λ = 0.4, 0.6, 0.8 in the SES implementation was employed. Figure 4 illustrates various approximations of the SES using the chosen values of λ. It is evident that as λ approaches 1, the SES becomes closer to the original time series, in line with expectations, thereby mitigating its underestimation bias.

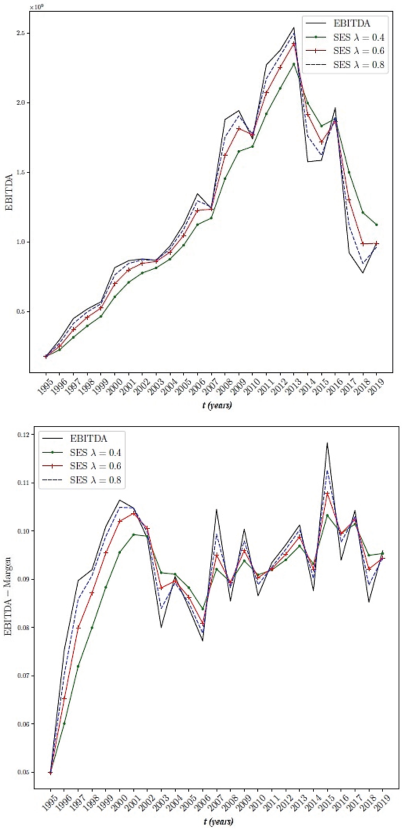

Figure 4. SES for EBITDA/EBITDA-Margin for Fashion industry in Colombia

SECOND ORDER EXPONENTIAL SMOOTHING

A Second Order or Double Exponential Smoothing (DES) can be applied when a bull or bear market is identified in the time series. Thus, High Order Exponential Smoothing allows to approximate the signal, using the following general polynomial approximation.

$$Y_T = \beta_0 - \beta_{1t} + \frac{\beta_{2t}^{2}}{2!} + \cdots + \frac{\beta_n}{n!} t^{n} + \varepsilon t \quad (7)$$

with the same conditions mentioned before for the noise εt, (n + 1)-order exponential smoothers can be applied to smooth the general polynomial of n degree

$$\begin{aligned} \bar{y}_T^{(1)} &= \lambda \bar{y}_T + (1-\lambda)\bar{y}_{T-1}^{(1)} \\ \bar{y}_T^{(2)} &= \lambda \bar{y}_T^{(1)} + (1-\lambda)\bar{y}_{T-1}^{(2)} \\ \bar{y}_T^{(n)} &= \lambda \bar{y}_T^{(n-1)} + (1-\lambda)\bar{y}_{T-1}^{(n)} \end{aligned} \quad (8)$$

For example, if the linear polynomial is considered to smooth possible linear trends, by considering the exponentially weighted smoother the facts, that $|1 - \lambda| < 1$ and $E(yt) = \beta_0 + \beta_1 t$ and the uncorrelated assumption, it can be shown that

$$E(Y_T) = (\beta_0 - \beta_{1T}) - \frac{1-\lambda}{\lambda}\beta_1 = E(Y_T) - \frac{1-\lambda}{\lambda} \quad (9)$$

which means the simple exponential smoother is a biased estimator, when considering a linear polynomial sign, as can be seen the bias amount correspond to $-(1 - \lambda)\,\beta 1/\lambda$, and on account of $-(1 - \lambda)\beta 1/\lambda \xrightarrow[\lambda \to 1]{} 0$ in this work λ closed to 1 are considered for a closer approximation λ = 0.99 can be employed.

As mentioned said above a DES can be obtain by applying simple exponential smoothing on $\bar{y}_T$ to get $\bar{y}_T^{(2)} = \lambda \bar{y}_T^{(1)} + (1-\lambda)\bar{y}_{T-1}^{(2)}$ with $\tilde{}\bar{y}_T^{(1)}$, $\bar{y}_T^{(2)}$ denoting first and second order smoothed exponentials, respectively. Due to DES is a first-order exponential smoother of the original first-order one: $E\left(\bar{y}_T^{(2)}\right) = E\left(\bar{y}_T^{(1)}\right) - \left(\frac{1-\lambda}{\lambda}/\beta_1\right)$ using this equation estimators for β0, β1 can be obtained

$$\begin{aligned} \beta_{1,T} &= \frac{\lambda}{\lambda - 1}\left(\bar{y}_T^{(1)} - \bar{y}_T^{(2)}\right) \\ \beta_{0,T} &= \left(2 - T\frac{\lambda}{\lambda-1}\right)\bar{y}_T^{(1)} - \left(1 - T\frac{\lambda}{\lambda-1}\right)\bar{y}_T^{(2)} \end{aligned} \quad (10)$$

the combination of these two estimators provide the predictor $Y_T = \beta_{0,T} + \beta_{1,T}T = 2\bar{y}_T^{(1)} - \bar{y}_T^{(2)}$. As can be seen in Figure 4, these bias error of the under- or over-estimation obtained with the SES is reduced reasonably using the DES.

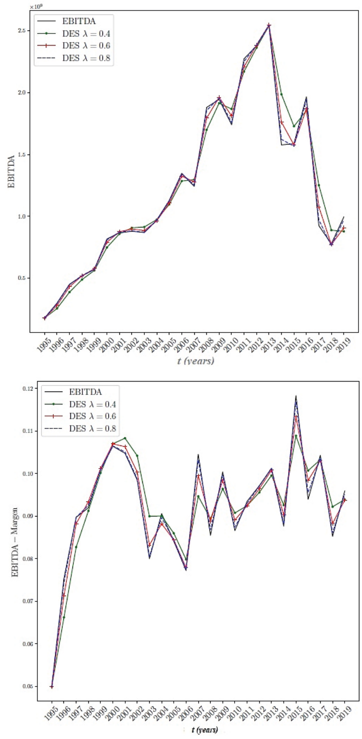

Figure 5. DES for EBITDA/EBITDA-Margin for Fashion industry in Colombia

HOLT'S EXPONENTIAL SMOOTHER

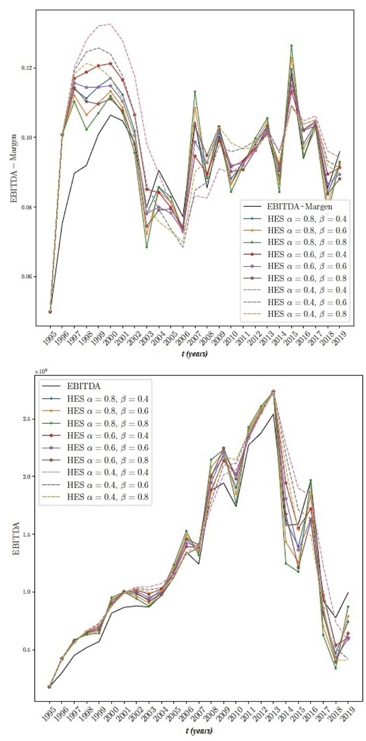

Figure 6. Holt's Exponential Smoothing EBITDA/ EBITDA-Margin for Fashion industry in Colombia

There is a double exponential smoothing method called Holt available in Python, and it can be imported from *statsmodels.tsa. api* packages. It is a bit different approach compared to the DES studied here and is based on the Holt's method, which divides the time series data into two parts: the level, Lt, and the trend, Tt, and can be used, when a bull or bear market is identified in the time series data.

As can be seen in Figure 6. Holt's Exponential Smoother HES shows higher under- and sub-estimation of the original time series.

THE COMPARISON OF EXPONENTIAL SMOOTHING MODEL

All the algorithms presented in this paper used Python. To investigate which approach has the best performance, error calculation was implemented using the mean absolute percentage error (MAPE), the mean absolute deviation (MAD) and the mean squared deviation (MSD) defined by the following expressions:

$$MAPE = \frac{\sum_{t=1}^{T} |(Y_t - \bar{y}_{t-1})/Y_t|}{T}$$
$$MAD = \frac{\sum_{t=1}^{T} |(Y_t - \bar{y}_{t-1})|}{T}$$
$$MSD = \frac{\sum_{t=1}^{T} (Y_t - \bar{y}_{t-1})^2}{T} \quad (11)$$

$$L_t = \alpha y_t + (1-\alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \beta(L_t - L_{t-1}) + (1-\beta)\, T_{t-1} \quad (12)$$

Table 1 reveals that DES and HES offer the highest performance and accuracy among all smoothing models applied to the EBITDA index, in line with our expectations. When we compare the error metrics for DES and HES, it becomes evident that HES with α = 0.4, β = 0.8 achieves the most accurate approximation for EBITDA smoothing, slightly outperforming DES for all values of λ and outperforming the other smoothing models. This superiority

Model	MAPE	MAD	MSD
SMA T = 2	2.563749e+01	2.886406e+08	1.425969e+17
SMA T = 4	3.187880e+01	3.502893e+08	1.838342e+17
SMA T = 8	4.249606e+01	4.804115e+08	3.261721e+17
SMA T = 16	4.419060e+01	5.567833e+08	4.570533e+17
SES λ = 0.4	3.057822e+01	3.361533e+08	1.708567e+17
SES λ = 0.6	2.443212e+01	2.720073e+08	1.343382e+17
SES λ = 0.8	2.208040e+01	2.502033e+08	1.250816e+17
DES λ = 0.4	2.299050e+01	2.548830e+08	1.265693e+17
DES λ = 0.6	2.142272e+01	2.444057e+08	1.228399e+17
DES λ = 0.8	2.051200e+01	2.353070e+08	1.271684e+17
HES α = 0.4 β = 0.4	2.072352e+01	2.345663e+08	1.387789e+17
HES α = 0.4 β = 0.6	1.983197e+01	2.305160e+08	1.264940e+17
HES α = 0.4 β = 0.8	1.902745e+01	2.253865e+08	1.212508e+17
HES α = 0.6 β = 0.4	1.974955e+01	2.301388e+08	1.249365e+17
HES α = 0.6 β = 0.6	1.953285e+01	2.314241e+08	1.297210e+17
HES α = 0.6 β = 0.8	2.005029e+01	2.410298e+08	1.406508e+17
HES α = 0.8 β = 0.4	1.982531e+01	2.348819e+08	1.408266e+17
HES α = 0.8 β = 0.6	2.186685e+01	2.632721e+08	1.603298e+17
HES α = 0.8 β = 0.8	2.420740e+01	2.945662e+08	1.873151e+17

TABLE 1. Error estimations for SES, DES and HES models for EBITDA index

Model	MAPE	MAD	MSD
SMA T = 2	1.203959e+01	1.138122e-02	2.039928e-04
SMA T = 4	1.285818e+01	1.198949e-02	2.112000e-04
SMA T = 8	1.265163e+01	1.168297e-02	2.069660e-04
SMA T = 16	1.048055e+01	9.591438e-03	1.612039e-04
SES λ = 0.4	1.244558e+01	1.151087e-02	2.049331e-04
SES λ = 0.6	1.229743e+01	1.131254e-02	1.877043e-04
SES λ = 0.8	1.204543e+01	1.108187e-02	1.819168e-04
DES λ = 0.4	1.284136e+01	1.183987e-02	2.064184e-04
DES λ = 0.6	1.215159e+01	1.117306e-02	1.872137e-04
DES λ = 0.8	1.186651e+01	1.085745e-02	1.827917e-04
HES α = 0.4 β = 0.4	1.582344e+01	1.483478e-02	3.546783e-04
HES α = 0.4 β = 0.6	1.391549e+01	1.301681e-02	2.765934e-04
HES α = 0.4 β = 0.8	1.354323e+01	1.258158e-02	2.399555e-04
HES α = 0.6 β = 0.4	1.388343e+01	1.294932e-02	2.510320e-04
HES α = 0.6 β = 0.6	1.350504e+01	1.252367e-02	2.299931e-04
HES α = 0.6 β = 0.8	1.353198e+01	1.247579e-02	2.295947e-04
HES α = 0.8 β = 0.4	1.464417e+01	1.359612e-02	2.576033e-04
HES α = 0.8 β = 0.6	1.462866e+01	1.355226e-02	2.700456e-04
HES α = 0.8 β = 0.8	1.513480e+01	1.399803e-02	3.004607e-04

TABLE 2. Error estimations for SES, DES and HES models for EBITDA Margin index

can be achieved by setting λ = 0.99 in DES. In particular, the effectiveness of HES is attributed to the two-part decomposition mentioned above.

Table 2 demonstrates that the DES model outperforms all other approaches used in this study. Unlike the EBITDA index, the EBITDA margin does not exhibit clear trends. Therefore, selecting the DES model over the HES model is the optimal choice for achieving a more accurate and refined forecasting model.

Tables 1 and 2 compare the percentage errors of three forecasting models: HES, DES, and HES for the EBITDA index. The tables provide error estimates, including the Mean Square Deviation (MSD), the Mean Absolute Deviation (MAD), and the Mean Absolute Percentage Error (MAPE).

Among these metrics, the DES model with λ = 0.8 produces the lowest MSD (127.16%), but also results in relatively high values of MAD (235.30%) and MAPE (205.12%). The HES model with α = 0.8 and β = 0.4 provides the best MSD (121.25%), with MAD at 225.38% and MAPE at 190.27%).

The HES model was tested using various combinations of alpha and beta values (0.4, 0.6, and 0.8) to determine the optimal approximation.

Therefore, the HES model is the most appropriate for predicting operating profits within the Colombian fashion industry between 1995 and 2019, according to the EBITDA index.

DISCUSSION AND LIMITATIONS

As discussed above, SES, HES and DES models are time series forecasting techniques used in different situations that need to be described from time series, and the choice between them depends on both the characteristics of the data and their performance.

Several models have been used for the simulations and predictions, although the ARIMA (Autoregressive Integrated Moving Average) model has not been used in this work, as the data present an additive seasonality. Tables 1 and 2, and figures 5 and 6 show an optimal performance of the HES and DES models for this type of analysis of time series data that present seasonality, as observed in the EBITDA index and EBITDA margin, allowing the objective proposed in the research to be achieved.

Examining the HES and DES models reveals distinct trends in the operating profit measured by the EBITDA index within the industry. Firstly, a progressive and incremental trend spans from 1995 to 2013. Analysing the corresponding EBITDA margin during this period indicates a parallel growth from 5% (1995) to 10.1% (2013). The second trend, observed from 2014 to 2019, illustrates a decline in the EBITDA index. However, the EBITDA margin demonstrates stability within the range of 8.9% (2014) to 9.6% (2019), with notable peaks at 11.9% (2015) and 10.3% (2017).

Addressing the research question on the impact of public policies on the Colombian fashion and garment industry, our analysis using two models reveals two discernible trends. The first, covering 1995 to 2013, shows a rebound in both the EBITDA ratio and the EBITDA margin. The second, covering 2014 to 2019, highlights a decline in the EBITDA ratio, accompanied by a seasonal pattern in the EBITDA margin.

The study systematically reviews national legislation to uncover trends and highlight policies that influence the industry's performance by modifying market regulations. In the first trend, it identifies the exchange statute (Law 9 of 1991) that supported Colombia's Economic Opening programme, initially lacking impact due to the industry's lack of preparedness, but oriented towards the domestic market from 1995 onwards. Subsequent measures facilitated garment exports to the United States, Venezuela and Colombia. In 1999, a policy aimed at boosting foreign trade operations and encouraging textile and clothing imports and domestic clothing exports (Decree 2685). Policies in 2001 allowed Customs Brokerage Companies to identify goods in Bonded Warehouses and Free Trade Zones (Decree 1232), leading to new businesses that facilitated imports and exports from 2002 to 2004. The 2005 adjustment reduced Liquid Assets, promoted Capitalisation and streamlined procedures for Customs Brokerage Companies (Decree 3600), encouraging new business in foreign trade.

In 2008, the boost to business dynamics in the foreign trade industry was consolidated, formalising the Shipping Authorisation and simplifying export procedures (Decree 1530). In addition, processes were optimised through the formalisation of documents such as the bill of lading and the cargo manifest (Decree 2101), and the conditions for the recognition and registration of Permanent Customs Users were simplified (Decree 2557). In 2009, this policy was complemented with the simplification of requirements for customs agencies (Decree 1510 and Resolution 1950), favouring the opening and facilitation of foreign trade operations. These measures encouraged manufacturing companies, including those in the fashion and clothing industry, to carry out direct import and export operations, promoting a continuous dynamic in subsequent years. In 2012, the optimisation of foreign trade was regulated, incorporating the use of irregular means and encouraging the creation of International Trading Companies (Decree 380). In addition, the Free Trade Agreement (FTA) between Colombia and the United States came into force, overcoming restrictions and expirations of bilateral agreements (Decree 993).

During the period 2013-2015, a second downward trend in EBITDA is observed, with a constant EBITDA margin (additive seasonality). In this context, it is possible to identify national policies that could have had an impact on the sustained growth of the industry. In 2013, two regulations introduced significant changes, such as the obligation for incumbent users to allocate spaces for customs authority officials, limiting the time of attention during daytime hours (Decree 602 of 2013). In addition, additional requirements were established for the accreditation of points of entry and exit of products, extending processing times for foreign trade operations (Decree 3059 of 2013). In 2015, the number of documents and formalities for customs inspection was increased, cancelling the 2008 simplification of cargo recognition (Decree 2101), and assigning more responsibilities to permanent or highly exporting customs users, complicating import and export processes and business (Decree 993 of 2015).

EBITDA peaked in 2013, highlighting the opportunities for both domestic and international sales with reduced tariff restrictions. This coincided with the implementation of the US Free Trade Agreement in 2012, which boosted exports to the US and resulted in an EBITDA margin of 10.1% - 0.9 percentage points higher than the overall average. It is worth noting that in 2015, the EBITDA margin of 11.9% was the highest for the period, despite an EBITDA of 1.6 billion pesos (approximately USD 508,000). This concentration of export activity within a specific producer group suggests a focus on local manufacturing and marketing specialisation.

The study has an additional limitation in using recent periods impacted by the gains obtained during the pandemic (2020-2021), whereby national policies were implemented on a territorial basis to address the health crisis. As a result, future research may need to approach the results of these years from a different perspective than solely examining the impact of public policies on the industry.

SUMMARY AND CONCLUSIONS

This study uses moving averages and exponential smoothing models to simplify the evaluation of two trends (1995-2013 and 2014-2019) within the Colombian fashion industry. It presents a summary of the factors and situations affecting industry companies between 1995 and 2019, examining significant events in government and the sector. Utilising time series data improves the precision of behaviour descriptions, enabling forecasts. Exponential smoothing techniques are used to predict EBITDA and study EBITDA margin allocation, providing valuable knowledge into possible future trends within the industry.

The study's findings reveal that the SMA and SES models yield high MAPE, MAD, MSD values (>20%) for both EBITDA and EBITDA margin. Conversely, the DES and HES models produce lower MAPE, MAD, MSD values (alpha, β = 0.4, 0.6, 0.8) for EBITDA, thereby demonstrating superior performance (<20%, MAPE, MAD, MSD, >10%). The optimal model for predicting and describing the EBITDA margin is the HES model with $\alpha = 0.4$, $\beta = 0.8$. Overall, this suggests that the DES and HES models are highly accurate in describing and predicting the actual profit of an industry (EBITDA) and its correlation with sales (EBITDA margin) in the Colombian fashion industry. The HES model, in particular, with $\alpha = 0.4$, $\beta = 0.8$, stands out as the most effective. This HES model serves as a reference guide for the Colombian government to determine actual profits within the industry. It aids in the establishment of both local and foreign trade policies, keeping in mind that higher company profits result in an increase in tax value.

This assessment has implications for government decision-making. Between 1995 and 2019, national policies were shown to have had a significant impact on the fashion and clothing industry in Colombia. Therefore, the financial performance of companies acts as a measure for governments to evaluate the consequences of such policies, leading local authorities to modify market regulations, including taxes, customs and control factors. These adjustments are carried out using practical techniques such as DES and HES to ensure effectiveness.

Further research could compare the results of this study with other methods, including deep learning, system dynamics, neural networks, or actor-based models, to obtain a more precise approach to predict the effects of policies on economic sectors and industries' earnings in Colombia. Furthermore, these methods could be applied in each Colombian region or province to extend the analysis.

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