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Propagation of best practices in value and supply chain management: Demand forecasting and planning

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Abstract

This paper is a discussion article that focuses on the propagation of best practices in value and supply chain management. Specifically, the article discusses the application of prudent demand analysis and forecasting techniques as tools for effective and efficient business management. The use of quantitative models such as time-series and econometric methods in forecasting prices, sales and demand volumes have formed the subject matter of the paper. The expeditious adoption of the techniques presented herein can equip the entrepreneur or manager with essential knowledge of future demand conditions that can be extremely useful when planning production schedules, inventory control, advertising campaigns, output in future periods, and investment, among other things. The ultimate expected impacts would be to facilitate the enhancement of economic and financial profitability, sustainability and other micro-economic and socio-economic performance variables.

Keywords: Forecasting; Qualitative; Quantitative; Time-series; Econometric; Demand

1. Introduction

A knowledge of future demand conditions can be extremely useful to managers when they are planning production schedules, inventory control, advertising campaigns, output in future periods, and investment, among other things. This paper will describe some techniques that managers can use to forecast future demand conditions. The range of forecasting techniques is so wide, and in this paper, we confine myself to a brief discussion of the more widely used techniques. For convenience, we divide forecasting methods into two groups: qualitative and quantitative models.

2. Qualitative models

A qualitative model is a model that does not employ explicit models or methods that can be replicated by another analyst. Qualitative models are more difficult to describe than statistical models since there exists no explicit model or method that can serve as a reference point. There is no model that can be used to replicate the initial forecast with a given set of data, and this feature, above all others, distinguishes this approach. In the final analysis, qualitative forecasts are often based on expert opinion. The forecaster examines the available data, solicits the advice of others, and then sifts through this amalgamation of evidence to formulate a forecast. The weights assigned to the various bits and pieces of information are subjectively determined and, we might add, separate the neophyte from the expert. [1]

2.1. Qualitative forecasting techniques

Qualitative forecasting methods are rather difficult to describe due to the subjective elements involved. While qualitative forecasts may indeed be the best technique, it is a challenging task to effectively disseminate this approach.

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In truth, we do not actually know how people are successful at qualitative forecasting. Because of their highly subjective nature, qualitative forecasting techniques will not be discussed here.

3. Quantitative models

In contrast, a quantitative model is a model that employs explicit models or methods that can be replicated by other analysts. The results of quantitative models can be reproduced by different researchers. An additional advantage of this approach is the existence of reasonably well-defined standards for evaluating such models. The final advantage of quantitative models is the ability to use them in simulation models. Basically, simulation models are models in which a researcher can obtain alternative forecasts for the future values of the endogenous variable, given alternative future trends in the exogenous variables. An endogenous variable is a variable whose value is determined by a system of equations (e.g. demand and supply that determine the price levels under perfect competition). An exogenous variable is a variable in a system of equations that is determined outside the system (e.g. the price determined by the manager of a price-setting firm under imperfect competition). Quantitative models can be further subdivided into two categories: time-series models and econometric models [2].

We begin with a sketchy discussion of qualitative forecasts and substantiate why in this paper they do not merit a detailed analysis. Next, we describe some basic time-series techniques. We then introduce econometric models and show (1) how to forecast future industry price and sales for price-taking firms and (2) how to forecast a future demand function for a price-setting firms. We conclude this paper with a note on some of the important problems involved in forecasting.

3.1. Time-series forecasting

Statistical forecasting is more analytical than qualitative forecasting because the models can be replicated by another researcher [3]. Statistical forecasting uses empirical data in basic statistical models to generate forecasts about economic variables [4]. There are two categories of statistical methods, namely time-series models and econometric models. We begin with a discussion of time-series models. A time-series model is a statistical model that shows how a time-ordered sequence of observations is generated. In general, a time-series model uses only the time-series history of the variable of interest to predict future values. Time-series models describe the process by which these historical data were generated [5].

3.1.1. Linear trend forecasting

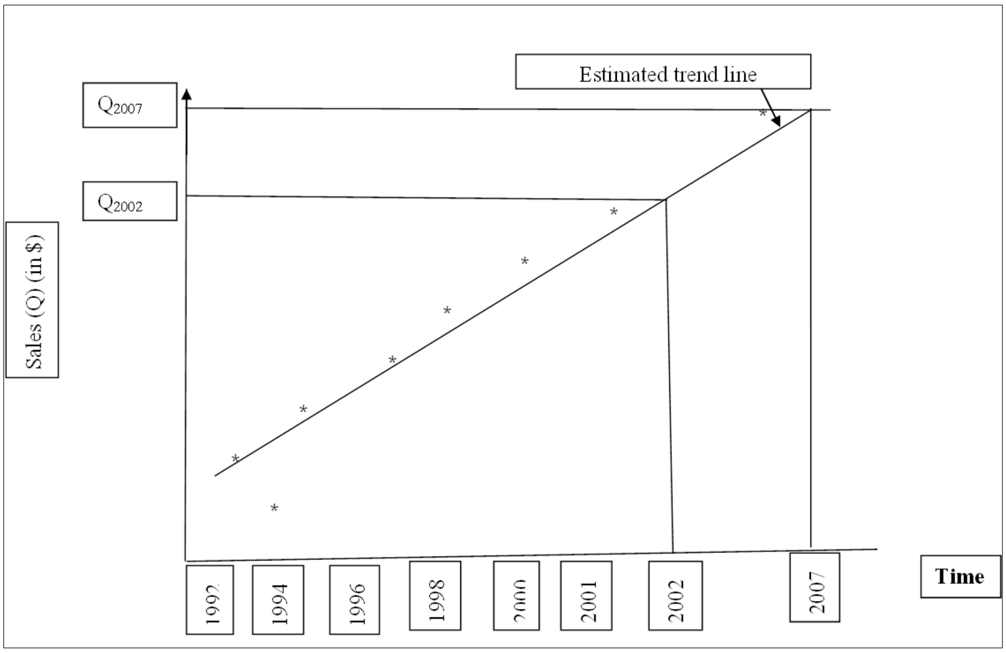

Figure 1 A linear trend forecast

A linear trend is the simplest time-series forecasting model. Using this type of model, one could posit that sales or prices increase or decrease linearly over time. For example, a firm's sales for the period 1992-2001 are shown by the 10 data points in Figure 1. The straight line that best fits the data, calculated using simple linear regression analysis, is illustrated by the solid line in the figure. The line of best fit indicates a positive trend in sales. Assuming that sales in the future will continue to follow the same trend, sales in any future period can be forecast by extending this line and picking the forecast value from the extrapolated line beyond the year 2001, for the desired future period. The sales forecasts for 2002 and 2007 (Q_{2002} and Q_{2007}) are shown in Figure 1.

Summarizing this procedure, we assumed that a linear relation between sales and time is given by the linear equation:

$$Q_t\text{^} = a + bt$$

Using the 6 observations for 1992 to 2001, we regress time ($t_{1992} = 1$; $t_{1993} = 2$; $t_{1994} = 3$; …, t_{2001}), the independent variable expressed in years, on sales, the dependent variable expressed in dollars, to obtain the estimated trend line:

$$Q_t\text{^} = a\text{^} + b\text{^}t$$

This line best fits the historical data. It is important to test whether there is a statistically significant positive or negative trend in sales. It is easy to determine if b**^** is significantly different from zero either by using a t-test for statistical significance or by examining the p-value for b**^**. If b**^** is positive and statistically significant, sales are trending upward over time. If b^ is negative and statistically significant, sales are trending downward over time. However, if b^ is not statistically significant, one would assume that b (the slope of the estimated trend line) = 0, and sales are constant over time. That is, there is no relation between sales and time, and any variation in sales is due to random fluctuations [6].

If the estimation indicates a statistically significant trend, you can then use the estimated trend line to obtain forecasts of future sales. For example, if a manager wanted a forecast for sales in 2002, the manager would simply insert 2002 into the estimated trend line, as follows:

$$Q\text{^}_{2002} = a\text{^} + b\text{^} \text{ x } (t_{2002})$$

3.1.2. A Sales Forecasting Example

In January 2002, Arnold Gwenzi started Terminator Pest Control, a small pest-control company in Harare, Zimbabwe.. Terminator Pest Control serves mainly residential customers citywide. At the end of March 2003, after 15 months of operation, Arnold decided to apply for a business loan from his bank to buy another pest-control truck. The bank was somewhat reluctant to make the loan, citing concern that sales at Terminator Pest Control did not grow significantly over its first 15 months of business. In addition, the bank asked Arnold to provide a forecast of sales for the next three months (April, May, and June). Arnold decided to do the forecast himself using a time-series model based on past sales figures. He collected data for the last 15 months. Sales were measured as the number of homes serviced during a given month. Since data were collected monthly, Arnold created a continuous time variable by numbering the months consecutively as January 2002 = 1; February 2002 = 2; and so on. The data for Terminator are shown in Table 1.

Table 1 Sales for Terminator Pest Control

Month	**t**	**Q_t**
January 2002	1	46
February 2002	2	56
March 2002	3	72
April 2002	4	67
May 2002	5	77
June 2002	6	66
July 2002	7	69
August 2002	8	79
September 2002	9	88
October 2002	10	91

November 2002	11	94
December 2002	12	104
January 2003	13	100
February 2003	14	113
March 2003	15	120

Arnold estimated the linear trend model:

$$Q_t = a + bt$$

and got the following results from the computer printout :

DEPENDENT VARIABLE: Q
OBSERVATIONS: 15
R-SQUARE: 0.9231
F-RATIO: 156.11
P-VALUE ON F: 0.0001

Table 2 T-test for Terminator Pest Control Company

Variable	Parameter estimate	Standard error	T-ratio	P-value
INTERCEPT	46.57	3.29	14.13	0.0001
T	4.53	0.36	12.49	0.0001

The t-ratio of the time variable, 12.49, exceeds the critical t of 3.012 for 13 degrees at the 1 percent level of significance (the values obtained by reading off critical t-values tables). The exact level of significance for the estimate 4.53 is less than 0.01 (or 1%), as indicated by the p-value. Thus, the sales figures for Terminator suggest a statistically significant upward trend in sales. Therefore, the estimated trend line can be used to obtain forecasts of future sales. As stated above, the linear trend model is:

$$Q_t = a + bt$$

From the above analysis, a, the intercept, was found to be 46.57, while the variable b was found to be 4.53. So the equation of the trend line (the line of best fit in the scatter diagram that could have been plotted of sales against time) can be re-written as:

$$Q = 46.57 + 4.53t$$

This linear trend model was then used by Arnold to estimate the sales forecasts for April 2003 (t =16), May 2003 (t=17), and June 2003 (t=18), as follows:

April 2003: Q^16 = 46.57 + (4.53 x 16) = 119
May 2003: Q^17 = 46.57 + (4.53 x 17) = 123.6
June 2003: Q^18 = 46.57 + (4.53 x 18) = 128.1

The bank decided to make the loan to Terminator Pest Control in light of the statistically significant upward trend in sales and the forecast of higher sales in the three upcoming months.

Thus, the linear trend method is a simple procedure for generating forecasts for either sales or price. Indeed, this method can be applied to forecast any economic variable for which a time series of observations is available.

3.2. Seasonal (or Cyclical) Variation

Time-series data may frequently exhibit regular, seasonal or cyclical variation over time, and the failure to take such regular variations into account when estimating a forecasting equation would bias the forecast. A seasonal or cyclical variation is the regular variation that time-series data frequently exhibit [7]. Frequently, when quarterly or monthly sales are being used to forecast sales, seasonal variation may occur. The sales of many products vary systematically by month or quarter. For example, in the retail clothing business, sales are generally higher before Easter and Christmas. Thus, sales would be higher during the second and fourth quarters of the year. The demand for woolen jerseys and winter jackets would also peak just before the onset of the winter season. In such cases, you would definitely wish to incorporate these systematic variations when estimating the equation and forecasting future sales. I now describe the technique most commonly employed to handle cyclical variation.

3.2.1. Correcting for seasonal variation using dummy variables

Consider the simplified example of a firm producing and selling a product for which sales are consistently higher in the fourth quarter than in any other quarter. Take an example of sales that occurred for four consecutive years, 1999, 2000, 2001, and 2002. Assume that the total sales for the year were larger for each consecutive year. In each of the four years, the data point in the fourth quarter is much higher than in the other three. While a time trend clearly exists, if the analyst simply regressed sales against time, without accounting for higher sales in the fourth quarter, too large a trend would be estimated (i.e. the slope would be too large). In essence, there is an upward shift of the trend line in the fourth quarter. Such a relation is presented in Figure 2. In the fourth quarter, the intercept is higher than in the other quarters. (Throughout this discussion, we assume that trend lines differ only with respect to the intercepts: the slope is the same for all the trend lines). In other words, a*, the intercept of the trend line for the fourth quarter data points, exceeds a, the intercept of the trend line for the data points in the other quarters. One way of specifying this relation is to define a* as a* = a + c, where c is some positive number. Therefore, the regression line we want to estimate will take the form:

$$Q_t = a + bt + c$$

where $c = 0$ in the first three quarters.

To estimate the preceding equation, statisticians use what is commonly referred to as a ***dummy variable*** in the estimating equation. A dummy variable is a variable that takes only values of zero (0) or one (1).

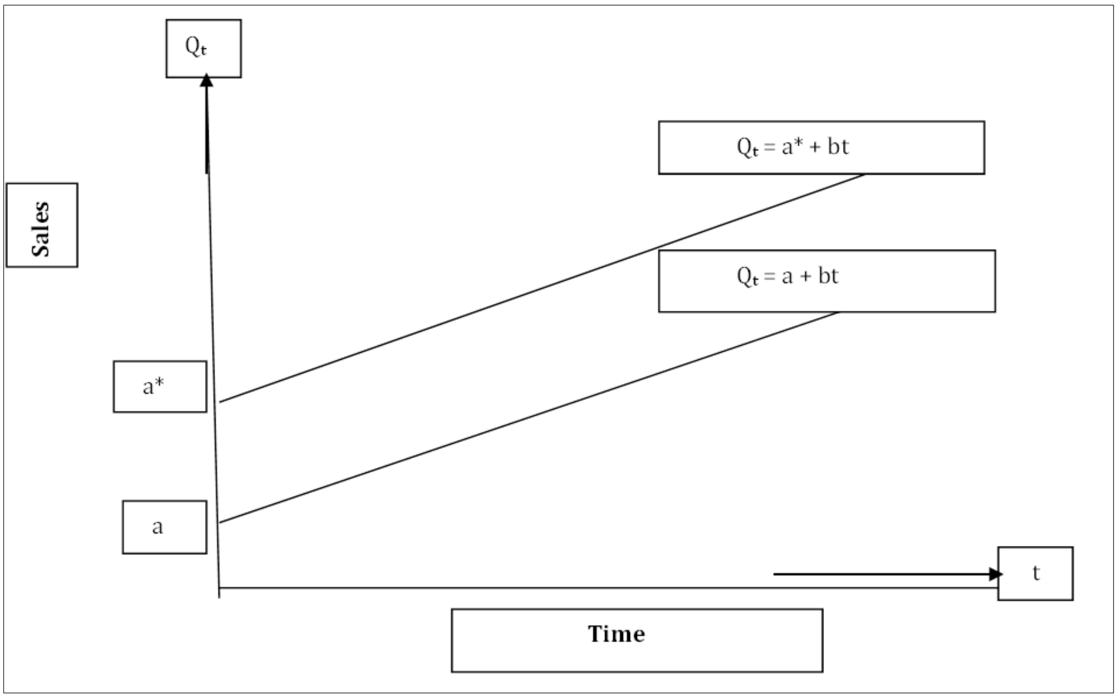

Figure 2 The effect of seasonal variation

In this case we would assign a dummy variable (D) of 1 if the sales observation is from the fourth quarter and zero in the other three quarters. The data are shown in Table 3 where Q_t represents the sales figure in the t^{th} period, and D = 1 for quarter IV and zero otherwise. Since quarterly data are being used, time is converted into integers to obtain a continuous time variable. Using these data, the following equation is estimated [8]:

$$Q_t = a + bt + cD$$

Table 3 Creating a dummy variable

Q_t	t	D
$Q_{1999[I]}$	1	0
$Q_{1999[II]}$	2	0
$Q_{1999[III]}$	3	0
$Q_{1999[IV]}$	4	1
$Q_{2000[I]}$	5	0
$Q_{2000[II]}$	6	0
$Q_{2000[III]}$	7	0
$Q_{2000[IV]}$	8	1
$Q_{2001[I]}$	9	0
$Q_{2001[II]}$	10	0
$Q_{2001[III]}$	11	0
$Q_{2001[IV]}$	12	1
$Q_{2002[I]}$	13	0
$Q_{2002[II]}$	14	0
$Q_{2002[III]}$	15	0
$Q_{2002[IV]}$	16	1

The above specification produces two equations like those shown in Figure 2. The estimated slope of the two equations would be the same. For quarters I, II, and III the estimated intercept is a^, while for the fourth quarter the estimated intercept is a^ + c^. This estimation really means that for any future period, t, the sales forecast would be:

$$Q_t\text{^} = a\text{^} + b\text{^}t,$$

Unless the period t occurs in the fourth quarter, in which case the sales forecast would be:

$$Q_t\text{^} = a\text{^} + b\text{^}t + c\text{^} = (a\text{^} + c\text{^}) + b\text{^}t$$

For example, referring to the data in Table 2, when a manager wishes to forecast sales in the third quarter of 2003, the manager uses the equation:

$$Q\text{^}_{2003[III]} = a\text{^} + b\text{^}\ (19)$$

When a manager wishes to forecast sales in the fourth quarter of 2003, the forecast is:

$$Q\text{^}_{2003[IV]} = (a\text{^} + c\text{^}) + b\text{^}\ (20)$$

In other words, when the forecast is for quarter IV, the forecast equation adds the amount 'c' to the sales that would otherwise be forecast. Going a step further, it could be the case that there exist quarter-to-quarter differences in sales (i.e. in Figure 2 there would be four trend lines). In this case, three dummy variables are used: D_1(equal to one in the first quarter and zero otherwise), D_2 (equal to one in the second quarter and zero otherwise), and D_3 (equal to one in the third quarter and zero otherwise). (Likewise, if there were month-to-month differences, 11 dummy variables would be used to account for the monthly change in the intercept. When using dummy variables, you must always use one less dummy variable than the number of periods being considered). Then, the manager estimates the equation:

$Q_t = a + bt + c_1D_1 + c_2D_2 + c_3D_3$

In quarter I the intercept is ($a + c_1$), in quarter II it is ($a + c_2$), in quarter III it is ($a + c_3$), and in quarter IV it is (a) only. To obtain a forecast of some future quarter, it is necessary to include the coefficient for the dummy variable for that particular quarter. For example, predictions for the third quarter of a particular year would take the form:

$Q_t\text{^} = a\text{^} + b\text{^}t + c_3\text{^}$

Perhaps the best way to explain how dummy variables can be used to account for cyclical variation is to provide an example.

3.2.2. The dummy variable technique: An example

Jean Maphosa, the sales manager of Nationwide Trucking Company, wishes to predict sales for all four quarters of 2003. The sales of Nationwide Trucking are subject to seasonal variation and also have a trend over time. Jean obtains sales data for 1992-2002 by quarter. The data are represented in Table 4.

Table 4 Quarterly sales data for Nationwide Trucking Company (1999-2002)

(1) Year	(2) Quarter	(3) Sales ($)	(4) t	(5) D_1	(6) D_2	(7) D_3
1999	I	72,000	1	1	0	0
	II	87,000	2	0	1	0
	III	87,000	3	0	0	1
	IV	150,000	4	0	0	0
2000	I	82,000	5	1	0	0
	II	98,000	6	0	1	0
	III	94,000	7	0	0	1
	IV	162,000	8	0	0	0
2001	I	97,000	9	1	0	0
	II	105,000	10	0	1	0
	III	109,000	11	0	0	1
	IV	176,000	12	0	0	0
2002	I	105,000	13	1	0	0
	II	121,000	14	0	1	0
	III	119,000	15	0	0	1
	IV	180,000	16	0	0	0

Note that since quarterly data are used, time is converted into a continuous variable by numbering quarters consecutively in column 4 of the table.

Jean knows, from a college course in managerial economics, that obtaining the desired sales forecast requires that she estimate an equation containing three dummy variables – one less than the periods in the annual cycle. She chooses to estimate the following equation:

$$Q_t = a + bt + c_1D_1 + c_2D_2 + c_3D_3$$

where D_1, D_2, and D_3 are, respectively, dummy variables for quarters I, II, and III.

(NB: This is only one of the specifications that is appropriate. Other equally appropriate specifications are

$$Q_t = a + bt + c_2D_2 + c_3D_3 + c_4D_4$$

$$Q_t = a + bt + c_1D_1 + c_3D_3 + c_4D_4$$

$$\text{or } Q_t = a + bt + c_1D_1 + c_2D_2 + c_4D_4$$

It is necessary only to have *any three* of the quarters represented by the dummy variables).

Using the data in Table 4, Jean estimates the preceding equation by means of regression analysis, and the results of this estimation are shown in the following computer printout (Table 5):

DEPENDENT VARIABLE: QT
R-SQUARE: 0.9965
F-RATIO: 794.126
OBSERVATIONS: 16
P VALUE ON F: 0.0001

Table 5 T-test for Nationwide Trucking Company

Variable	**Parameter estimate**	**Standard error**	**T - ratio**	**P - value**
INTERCEPT	139625.0	1743.6	80.8	0.0001
T	2737.5	129.96	21.06	0.0001
D1	-69788.0	1689.5	-41.31	0.0001
D2	-58775.0	1664.3	-35.32	0.0001
D3	-62013.0	1649.0	-37.61	0.0001

Upon examining the estimation results, Jean notes that a positive trend in sales is indicated ($\hat{b} = 2737.5 > 0$). In order to determine whether the trend is statistically significant, either a t-test can be performed on $\hat{b}$ or the p-value for $\hat{b}$ can be assessed for significance. The calculated t-value for $\hat{b}$ is = 21.06. With 16-5 = 11 degrees of freedom (degrees of freedom are the number of observations in the sample minus the number of parameters being estimated by the regression analysis), the critical value of t is 2.201, as can be read for the critical t-value table. Since 21.06 > 2.201, $\hat{b}$ is statistically significant. The p-value for b is so small (0.01 percent) that the chance of making a Type I error – incorrectly finding significance – is virtually zero.

Next, Jean calculates the estimated intercepts of the trend line for each of the four quarters. In the first quarter:

$$\hat{a} + \hat{c}_1 = 139{,}625 - 69{,}788 = 69{,}837$$

In the second quarter:

$$\hat{a} + \hat{c}_2 = 139{,}625 - 58{,}775 = 80{,}850$$

In the third quarter:

$$\hat{a} + \hat{c}_3 = 139{,}625 - 62{,}013 = 77{,}612$$

In the fourth quarter,

$$\hat{a} = 139{,}625.$$

These estimates indicate that the intercepts, and thus sales, are lower in quarters I, II, and III than in quarter IV. The question that always must be asked is: Are these intercepts *significantly* lower?

To answer this question, Jean decides to compare quarters I and IV. In quarter I, the intercept is $\hat{a} + \hat{c}_1$; in quarter IV, it is $\hat{a}$. Hence, if $\hat{a} + \hat{c}_1$ is significantly lower than $\hat{a}$, it is necessary that $\hat{c}_1$ be significantly less than zero. That is, if $\hat{a} + \hat{c}_1 < \hat{a}$, it follows that $\hat{c}_1 < 0$. Jean already knows that $\hat{c}_1$ is negative; to determine if it is significantly negative, she can perform a t-test. The calculated value of t for $\hat{c}_1$ is -41.31(see computer printout). Since this absolute value (ignoring the negative sign) > 2.201 (the critical value of t, for 11 degrees of freedom and using a 5% level of significance, as can be read from the critical t-values table), $\hat{c}_1$ is significantly less than zero. This indicates that the intercept – and the sales – in the first quarter is *significantly* less than in the fourth quarter. Similar analytical comparisons between the second quarter and the fourth quarter; and between the third quarter and the fourth quarter, show that the intercepts in the second and third quarters are significantly less than the intercept in the fourth quarter. Hence, Jean has evidence that there is a significant increase in sales in the fourth quarter.

She can now proceed to forecast sales by quarters for 2003. In the first quarter of 2003, t = 17, $D_1 = 1$, $D_2 = 0$, and $D_3 = 0$. Therefore, the forecast for sales in the first quarter of 2003 would be:

$$Q_t = \hat{a} + \hat{b}\,t + \hat{c}_1 D_1 + \hat{c}_2 D_2 + \hat{c}_3 D_3$$

$$Q_{2003[I]} = \hat{a} + (\hat{b} \times 17) + (\hat{c}_1 \times 1)$$

$$= 139{,}625 + (2{,}737.5 \times 17) - 69{,}788 = 116{,}374.5$$

Using precisely the same method, the forecasts for sales in the other three quarters of 2003 are as follows:

$$Q_{2003[II]} = \hat{a} + \hat{b} \times 18 + \hat{c}_2$$

$$= 139{,}625 + (2{,}737.5 \times 18) - 58{,}775$$

$$= 130{,}125$$

$$Q_{2003[III]} = \hat{a} + (\hat{b} \times 19) + \hat{c}_3$$

$$= 139{,}625 + (2{,}737.5 \times 19) - 62{,}013$$

$$= 129{,}624.5$$

$$Q_{2003[IV]} = \hat{a} + (\hat{b} \times 20)$$

$$= 139{,}625 + (2{,}737.5 \times 20)$$

$$= 194{,}375$$

In this example, we have confined our attention to quarterly variation. However, exactly the same techniques can be used for monthly data or any other type of seasonal or cyclical variation. In addition to its application to situations involving seasonal or cyclical variation, the dummy-variable technique can be used to account for changes in sales (or any other economic variable that is being forecast) due to forces such as wars, bad weather, or even strikes at a competitor's production facility.

3.3. Econometric models

Another method used in statistical forecasting and decision making is econometric modeling. The primary characteristic of econometric models, which differentiates this approach from preceding approaches, is the use of an explicit structural model that attempts to explain the underlying economic relations. More specifically, if we wish to employ an econometric model to forecast future sales, we must develop a model that incorporates the variables that actually determine the level of sales (e.g., income, the price of substitutes, etc.). This approach differs from the qualitative approach and the time-series approach.

The use of econometric models has several advantages. First, econometric models require analysts to define explicit causal relations. This specification of an explicit model helps eliminate problems such as spurious (false) correlation between normally unrelated variables and may make the model more logically consistent and reliable.

Second, this approach allows analysts to consider the sensitivity of the variable to be forecasted to changes in the exogenous explanatory variables. Using estimated elasticities, forecasters can determine which of the variables are most important in determining changes in the variable to be forecasted. Therefore, the analyst can examine the behaviour of these variables more closely.

Econometric forecasting can be utilized to forecast either future industry price or quantity for price-taking firms. One of the most widely used econometric models to forecast future sales is the regression analysis forecasting model [8].

3.3.1. Simple linear regression model

Simple linear regression relates one dependent variable to one independent variable in the form of a linear equation expressed simply as:

$$y = a + bx$$

where y is the dependent variable

a is the intercept on the y – axis
b is the slope of the linear regression line, and
x is the independent variable.

Typically, the dependent variable (y) is plotted on the vertical axis and the independent variable (x) is plotted on the horizontal axis. Graphically, simple linear regression is expressed as follows (Figure 3).

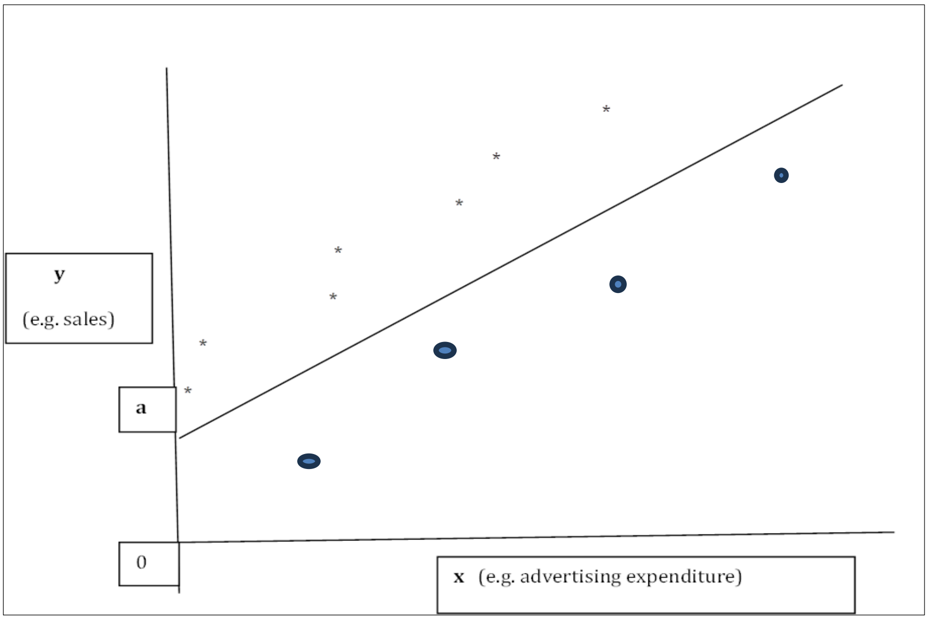

Figure 3 Sales and expenditure relationship

The intercept (a), is a constant that represents the value of (y) when (x) is zero. As such, the intercept indicates the point at which the linear equation will intercept (i.e. intersect with) the (y) axis. When given a list of paired (x) and (y) values, the two components in the regression that must be computed in order to come up with a regression equation for these values are (a), the intercept, and (b), the slope. The slope represents the change in (y) per unit change in (x). For example, each increase in advertising expenditure results in a corresponding increase in sales, the magnitude of which is determined by the slope. It can be shown that (a) and (b) are computed using the following formulas:

$$\mathbf{a = \bar{y} - b\bar{x}} \quad \text{...(1)}$$

$$\mathbf{b = [\sum xy - n\bar{x}.\bar{y}]/[\sum x^2 - n\bar{x}^2]} \text{.........................(2)}$$

where

n = the number of pieces of data

$\bar{x}$ **= (∑x)/n** = the mean of the x data ……………(3)

$\bar{y}$ **= (∑y)/n** = the mean of the y data ……………(4)

The following table gives hypothetical **x** and **y** data, where **x** data are the independent values (expenditures on advertising), and **y** data are the dependent values (sales of the advertised item).

Table 6 Sales and expenditure relationship

Year	x ($)	y ($)	xy ($) (000)	x^2 ($) (000)
1995	5 700	7 000	39 900	32 490
1996	5 500	10 000	55 000	30 250
1997	6 500	9 000	58 500	42 250
1998	9 000	12 000	108 000	81 000
1999	6 900	8 000	55 200	47 610
2000	8 100	14 000	113 400	65 610
2001	9 500	15 000	142 500	90 250
2002	10 200	17 000	173 400	104 040
2003	8 200	16 000	131 200	67 240
2004	10 600	18 000	190 800	112 360
∑	80 200	126 000	1 067 900	673 100

First, we will compute the slope of this equation (b).

To compute $\bar{x}$, substitute the values of ∑x and n in equation (3) above, to obtain

$$\bar{x} = (\sum x)/n = \$80{,}200/10 = \$8{,}020$$

To compute $\bar{y}$, substitute the values of **∑y** and **n** in equation (4) above, to obtain

$$\bar{y} = (\sum y)/n = \$126{,}000/10 = \$12{,}600$$

To compute (b), substitute the values of **∑xy, n,** $\bar{x}$, $\bar{y}$, **∑x²**, and $\bar{x}^2$ in equation (2) above, to obtain:

$$\mathbf{b} = [\sum xy - n\bar{x}.\bar{y}]/(\sum x^2 - n\bar{x}^2) = \frac{\$[1{,}067{,}900{,}000 - (10)(8{,}020)(12{,}600)]}{\$[673{,}100{,}000 - (10)(8{,}020)^2]}$$

$$\mathbf{b} = 57{,}380{,}000 / 29{,}896{,}000 = \mathbf{1.91}$$

Now that we know **b**, we can compute the intercept of our regression equation, **a,** by

substituting the values of $\bar{y}$, **b**, and $\bar{x}$ in equation (1) above, to obtain:

$$\mathbf{a} = \bar{y} - b\bar{x} = 12{,}600 - (1.91)(8{,}020) = \mathbf{-2{,}718}$$

Thus, our **simple linear regression equation** (**y = a + bx**) is **y = - 2,718 + 1.91x**

Now, the sales manager can use the regression equation to forecast sales for a specific expenditure on advertising. For example, if the business spends $10,000 on advertising (i.e., **x** = 10,000), the forecasted sales (y) are computed as:

$$\mathbf{y} = -\ 2{,}718 + 1.91\ (10{,}000) = -2{,}718 + 191{,}000 = \mathbf{\$188{,}282}$$

4. Conclusion

This paper focused on the propagation of best practices in value and supply chain management. Specifically, the article discussed the application of prudent demand analysis and forecasting techniques as tools for effective and efficient business management. The use of quantitative models such as time-series and econometric methods in forecasting prices, sales and demand volumes have formed the subject matter of the paper. The expeditious adoption of the techniques presented herein can equip the entrepreneur or manager with essential knowledge of future demand conditions that can be extremely useful when planning production schedules, inventory control, advertising campaigns, output in future periods, and investment, among other things. The ultimate expected impacts would be to facilitate the enhancement of economic and financial profitability, sustainability and other micro-economic and socio-economic performance variables.

Compliance with ethical standards

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Disclosure of conflict of interest

There is no conflict of interest among the authors or stakeholders of this work.

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