International Journal of Business Marketing and Management (IJBMM)
Volume 6 Issue 4 April 2021, P.P. 42-52
ISSN: 2456-4559
www.ijbmm.com

Forecasting accuracy of industrial sales with endogeneity in firm-level data

Adriana Bruscato Bortoluzzo[1], Danny Pimentel Claro[2]
[1](Quantitative Methods / Insper, Brazil)
[2](Marketing / Insper, Brazil)

ABSTRACT : *Over- or underestimating sales is detrimental to marketing and sales efforts as well as inventories and cash flow management. Thus the purpose of this investigation is to evaluate the forecasting accuracy of three competing multivariate time-series models that take into account existing endogeneity in monthly firm-level data from an industrial manufacturing firm. Two-stage least squares transfer function model including instrumental variables, Vector Autoregressive (VAR) model and Bayesian VAR are estimated and their forecasting performances are compared to an autoregressive moving average model (benchmark). using out of sample error measures. According to forecasting accuracy measures, models that take into account endogeneity outperform the benchmark. They also performed better when applied to data that includes the 2008 financial crisis, reinforcing the use of these proposed models in turbulent times to forecast sales. Only a little effort has been made in companies to model the endogeneity of the data, however great are the gains in sales forecasting with such statistical tools. Whatever the company, these models can be applied since there exists historical data. Previous literature in management has resorted to standard time series forecasting techniques, but has not employed models that accommodate potential endogeneity among the explanatory variables in firm-level data. Marketing effort affects sales as well as managers' decisions regarding marketing investments and project proposals can also be affected by sales.*

KEYWORDS - *Industrial sales, Forecasting, Endogeneity, Time series*

I. Introduction

Firms of industrial products use sales forecasting to operate efficiently and meet customer demand. Substantial over- or underestimates of demand can cause serious problems in various firm's management areas [1]. Forecasting sales volume is crucial for creating operating budgets, which play an important role in a firm's internal planning, motivation and performance management functions [2]. Industrial products primarily constitute those used in the production of other products and are customized using a 'made to order' approach. Inaccurate forecasting affects a range of a manufacturer's activities from delivery schedules to capacity loss due to overstocking, suboptimal capacity utilization and excessive and obsolete inventory [3]. The inaccurate forecasts influence negatively efficiency and sales performance. Given the relevance of this issue, industrial sales forecasting has been studied by researchers and addressed in various ways.

The majority of previous studies focusing on sales forecasting models sought to explain sales behavior by examining time series of internal manufacturer variables, such as marketing expenses [4]. [5] and [6] demonstrated the importance of macroeconomic variables (e.g., price, demand, exchange rate) to forecast a firm's sales in the consumer market. These variables have also been included in studies of industrial markets [7]. In the auto-parts industry, forecasting models are a component of complex support systems that need to be parsimonious with respect to variable selection due to the cost of collecting and treating the data [8]. Even for small firms, [9] showed that using a formal sales forecasting framework there is a gain, and they applied a Bayesian decision theory in the production of sales forecasts.

Industrial products require particular attention of sales forecasting models. [10] noted differences between the statistical approaches applied to consumer products and the statistical approaches applied to industrial products. Sales forecasts in industrial markets are also modified using the opinions of the sales team and management [4], [13]. [14] highlighted this tendency and found that only 6% of the 300 industrial firms sampled used regressions as part of their forecasting method. [15] suggested that the accuracy of sales volume forecasting can be improved by using statistical models in lieu of simple personal opinions that may be affected by qualitative considerations and political maneuvering intended to appease conflicting objectives within the firm. As an example, forecasts based on opinions can show negative bias, particularly if a fraction of the sales team's income or performance targets were linked to exceeding expected values [10]. In addition, research has indicated that attempting to encourage the sales team to participate in forecasting is innocuous because linking the forecast to the sales team's input has no significant, positive influence on forecast accuracy [11]. While the task is difficult, recent research has concentrated on modeling the effect of the opinions and judgment of managers on improving the effectiveness of sales forecasts [12].

Previous studies have considered a range of variables to forecast sales, both managerial and economic, and treated these variables as exogenous. However, various management decisions affect sales and the decisions are also intimately affected by sales expectations. For instance, marketing investment decisions have a causal effect on sales outcomes, and sales outcomes simultaneously affect marketing investment decisions. An endogenous variable is both an input and an output variable. We believe that econometric models that properly account for these important interrelationships may perform superiorly than standard models regarding sales forecasting.

The main objective of this paper is to evaluate the forecasting accuracy of three competing multivariate time-series models that take into account existing endogeneity: (1) two-stage least squares transfer function model (2SLSTF) including instrumental variables, (2) vector autoregressive model (VAR) and (3) Bayesian vector autoregressive model (BVAR). An autoregressive moving average model (ARMA) was estimated as a benchmark for the forecasting comparisons. We calculate the out of sample root mean squared error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE) to evaluate the relative performance of the estimated models.

The paper makes two contributions. First, the data set used to estimate the models include firm-level data as well as industry and economic public data. This is a unique data structure of industrial products that represents the sales settings and includes relevant variables to forecasting (e.g., [16]). The firm level variables include marketing expenditure and sales acquisition measurement (i.e. proposals). The data also include economic variables such as reference rate, stock market index and exchange rate.

Second, the results show that the multivariate models are more accurate than the univariate ones, specially the 2SLSTF model that outperforms the other models according to forecasting accuracy measures. The results illustrate the importance of properly addressing endogeneity in industrial sales forecasting. The 2SLSTF model also performed better when applied to data from the 2008 financial crisis, reinforcing the importance of economic variables in such turbulent contexts [5], [17].

The remainder of the article proceeds as follows. In Section 2, there is a descriptive analysis of the data. In Section 3, a detailed description of the models to forecast industrial sales is presented. In Section 4, it is discussed the final versions of the models and their forecasting performance is compared. Finally, Section 5 concludes the paper.

II. Data description

The firm-level data were collected from the sales records of a European firm operating in South America. This operation has a leading position in the market. We selected the best-selling product (between 45% and 55% of total sales), which is made to order with a set of core components and one customized component to meet customers' needs and is applied in a wide variety of industries (e.g., mining, steel, pulp and paper, automotive, oil and gas, power generation, textiles, food). In South America, we focused on Brazil, which is the most representative market and hosts the largest plant in operation outside Europe. The Brazilian government requires a minimum of 60% local content in these products, prohibiting direct imports and creating local investment incentives. Once they have met this condition, customers are able to access investment capital with low interest rates and an extended repayment period. The firm's marketing campaigns generate product awareness and highlight the product mix and integrated service features. Customers are accessed through major industry trade shows and advertisements in specialized magazines and websites. A dedicated and stable (i.e., low turnover) sales force engages in face-to-face selling and reinforces marketing efforts. The sales force visits customers and develops customized offers to effectively satisfy customers' needs.

Table 1 presents a description of the variables that are used in this study. The forecasting variable is monthly sales volume from January 2004 to April 2012 (n=100 observations). This time series includes the 2008 financial crisis and the years 2009 and 2010, when substantial government incentives were implemented to support investments across a wide variety of industries in which the firm's customers operate. This data set represents industrial product context and is set up similarly to other data sets (e.g., [16]). Unfortunately, the company only allows the use of real data after 6 years of its occurrence, however this does not invalidate the modeling techniques or the contributions of the article that are timeless (data are available upon request).

The explanatory variables were mainly drawn from existing forecasting and industrial marketing literature. The variables are divided into two sets: endogenous and exogenous. Two explanatory variables (proposals and marketing) were identified as endogenous because they are expected to have a bidirectional relationship with sales volume. The variable 'proposals' captures the number of project proposals that the sales force develops for customers each month. The firm considers this indicator when future sales and purchases of input supplies are predicted. The variable 'marketing' captures monthly investments in advertisements in specialized media, the sales force's promotional materials and spending on industry trade shows and mobile showrooms.

Seven explanatory variables were identified as exogenous. The variable 'reference rate' is the main reference rate for investment capital loans, which are provided by the national central bank. A 'confidence index' was included to capture a subjective measure of economic activity, and a 'stock market' index provides an objective measure of such activity. We also included an 'exchange rate' variable (BRL/USD) and two variables that account for the incentive programs that the government provides to industries: total BNDES (government bank to foster economic development) loan volume and the BNDES loan program with reduced interest rates (PRI). Finally, we accounted for foreign direct investments in industrial plant production (FDI).

Table 1. Variables' Description

Variable	Description	Source
Endogenous		
Sales Volume	Sales volume treated, in millions of R$	Firm Records
Proposals	New proposals of sales (short, medium and long run)	Firm Records
Marketing	Total marketing spending, in thousands of R$	Firm Records
Exogenous		
Reference Rate	SELIC interest rate	http://www.ipeadata.gov.br/
Confidence index	Industrial confidence index ICI-FGV	http://portalibre.fgv.br
Stock Market	BM&F-Bovespa market index	http://www.bmfbovespa.com.br
Exchange Rate	Exchange rate (R$/US$). monthly average of bid level	http://www.ipeadata.gov.br/
BNDES loans	BNDES total loan volume, in million R$	http://www.bndes.gov.br/
PRI	BNDES – loan program with low interest rates (dummy variable)	http://www.bndes.gov.br/
FDI	Foreign direct investment (FDI)	http://www.ipeadata.gov.br/

The variables sales volume, marketing, BNDES loan volume and FDI were deflated through the use of the national index of market prices (IGPM). which is calculated by the Getulio Vargas Foundation on a monthly basis. We considered the period from November 2008 to July 2010, when the Brazilian economy was more influenced by the subprime crisis. To reduce the effect of the crisis on several sectors of the Brazilian economy, including industrial products manufacturers, the government provided incentives for purchasing industrial products and reduced the interest rate charged for loans (PRI) for this purpose from July 2009 to March 2011.

Figure 1 shows descriptive graphs of the variables considered and allows us to establish some patterns. For instance, the reference rate is negatively correlated with sales, which makes economic sense. In the period following the outbreak of the 2008 crisis (Nov/2008-Jul/2010). increases in the reference rate and exchange rate occurred. The confidence index, the stock market index and the FDI also declined just prior to the decline in sales. Thus, these economic variables may be useful in forecasting the behavior of sales during the crisis period. Moreover, regarding the government incentive programs, an increase in sales is associated with increasing BNDES loan volume. The government's incentive generated a notable increase in sales of industrial products, while FDI comes right after increases in sales.

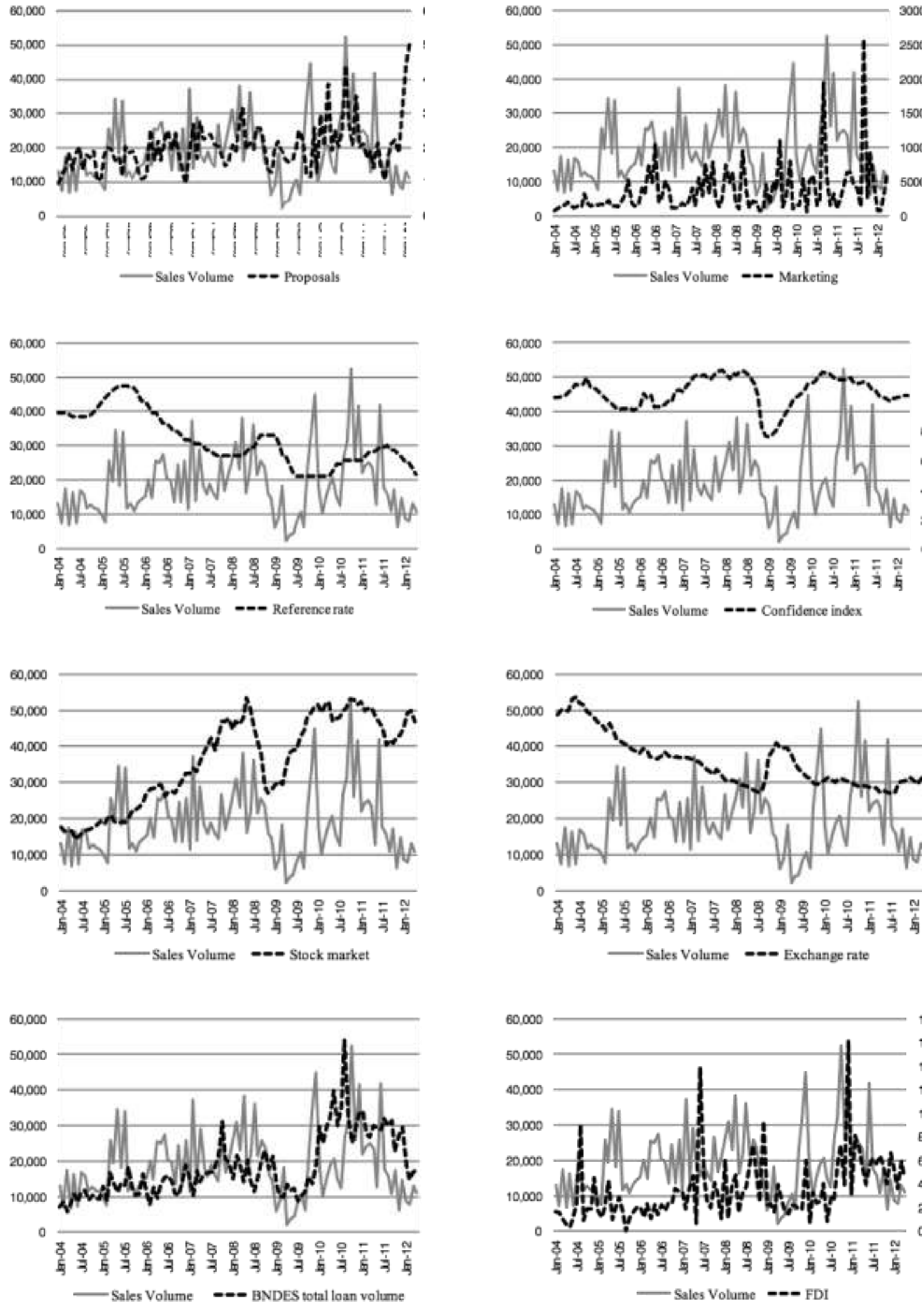

Figure 1. Descriptive Graphs of the Time Series (Sales is on the Left Axis)

Table 2 summarizes the time-series data considered in the analysis, specifically the average of each variable by year. Sales volume varies over time, with a decline in the crisis period (2008-10) and a recovery soon after. The average number of proposals was approximately 200 per month, while average spending on marketing was approximately $35 thousand per month. A sharp increase in proposals occurred in 2012, nearly doubling the figures in the preceding months, which may reflect the increase in marketing expenses in the previous year.

Table 2. Descriptive Analysis of Time Series per Year

Variable	**Year**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**
Sales	Mean	12,358	17,694	20,424	19,964	24,487	14,185	24,046	19,291	10,153
	SD	3,777	9,083	5,182	7,473	7,534	13,355	12,610	9,132	2,347
Proposals	Mean	152	165	186	202	217	177	254	194	362
	SD	36	34	51	51	49	43	86	61	143
Marketing	Mean	15,210	21,295	39,673	33,477	36,283	35,558	45,676	60,369	27,539
	SD	6,088	10,976	27,060	24,033	27,656	31,786	50,571	66,298	25,862
Reference rate	Mean	16.3	19.1	15.4	12.1	12.4	10.1	9.9	11.8	9.9
	SD	0.4	0.7	1.5	0.8	1.1	1.8	0.9	0.5	0.7
Confidence index	Mean	108	99	101	116	110	94	116	107	104
	SD	4	5	4	4	15	12	2	5	1
Stock market	Mean	22,323	27,543	38,081	53,213	55,329	52,748	67,290	61,348	63,791
	SD	1,730	2,807	2,339	7,278	12,083	10,303	2,766	5,647	2,722
Exchange rate	Mean	2.9	2.4	2.2	1.9	1.8	2.0	1.8	1.7	1.8
	SD	0.1	0.2	0.0	0.1	0.3	0.2	0.0	0.1	0.1
BNDES Loans	Mean	153	220	216	303	299	209	549	484	285
	SD	29	48	51	84	60	49	131	49	28
FDI	Mean	2,244	1,774	2,177	3,842	4,452	2,525	4,386	5,667	4,883
	SD	2,376	1,035	769	3,427	2,357	1,280	4,160	1,387	972

Note: 2012 is From January to April

We assessed the stationarity of each time series through the use of correlograms and the augmented Dickey–Fuller (ADF) unit root test. We were then able to select the appropriate transformations and variables for use in the forecasting models. The correlogram of the forecasting variable, sales volume, exhibited exponential decay toward zero in the autocorrelation function (ACF). and on the basis of the ADF test, we did not find evidence of a unit root at the 1% significance level. Furthermore, sales volume did not present any indication of seasonality, which reinforces the trend in this variable over time reported in Figure 1. Following the same arguments, we also assumed that proposals, marketing and BNDES loan volume have no unit root. We only applied the natural logarithm transformation (log) to these variables to stabilize their variance.

The correlograms of the other five variables (reference rate, confidence index, stock market, exchange rate and FDI) exhibit a slow decay in the ACF and a value close to 1 for the first lag partial autocorrelation function (PACF) coefficient. In addition, the ADF tests provided evidence of a unit root, even at the 10% significance level. Therefore, we applied the log first difference to these variables before we estimated the models. The log first difference becomes equal to the difference between the log of the variable at times t and t-1 for t=2,…,T.

III. Model estimation

3.1 Modeling endogeneity

Sales forecasting in manufacturing firms involves several decision-making processes that require accurate modeling to select the proper actions in the areas of production and sales planning. Prior studies have devoted particular attention to how forecasting can be improved through carefully examination of management judgmental adjustment [12]. decision support systems [18] and process to develop forecasting systems [16]. The majority of past studies have failed to consider that managers make decisions not randomly but based on their expectations of how their choices will affect future sales [19]. Therefore, management's decisions are predicated on the notion that these decisions are endogenous to the sales performance outcome that they expect.

[20] placed the endogeneity as a threat to the validity of the results achieved in marketing research and they discussed the statistical solutions to this problem. Endogeneity has also implications for the statistical analysis of sales forecasting. Failing to account for endogeneity in the estimation may cause biased coefficient estimates [21]. [22] showed that estimations that do not address endogeneity produce parameter estimates that are likely to be biased and may therefore yield erroneous results and incorrect conclusions regarding the veracity of theory. This bias results from omitted variables that affect both the influencing factors and sales outcomes. Estimating unbiased coefficients in the presence of such problems requires statistical approaches that account for the omitted variables. Previous studies have used vector autoregressive models (VAR) and vector error correction models (VECM) to account for endogeneity in time-series data [23]. This type of cointegration analysis addresses the problem of spurious regressions among nonstationary time series. VECM elucidate potential interrelationships among variables over time, while reducing the risk of endogeneity bias. Other studies have employed discrete-choice econometric modeling approaches and their corresponding outcome variables to address endogeneity [24]. [25] suggested incorporating the possibility of self-selection to address the extent to which an individual's professional choices are influenced by and influence his or her income.

Transfer functions have long been used to forecast time series concerning economic and monetary issues [26]. To account for endogeneity, econometricians have applied two-stage least squares (2SLS) to estimate parameters in systems of linear, simultaneous equations and address endogenous variable bias in single-equation estimation (e.g., [27]). [28] provided one of the first thorough elaborations of 2SLS estimation, which is now included in every econometrics textbook (e.g., [21]). The model specification requires one or more instrumental variables (IVs) that affect the influencing factor and do not directly affect sales performance. For many cross-sectional data sets, finding IVs that affect the influencing factors but not performance is difficult [29]. In some cases, one might seek out variables associated with government investment policies that differ across regions and that might affect the decision, for instance, regarding the number of project proposals. Time series data on management decisions allow us to identify the instruments of interest under less subjective assumptions than cross-sectional data. IVs are required to address the simultaneous causality among variables, and the inferences made using these models are straightforward [30]. Therefore, a 2SLSTF model would provide a more accurate estimation of time series that contain endogenous variables.

1.2 Forecasting models

We estimate and compare the results of three classes of time-series models: ARMA, transfer function (TF) and both classic and Bayesian VAR. We applied a log first difference transformation to the variables presenting evidence of a unit root, as described in the previous section. The ARMA model is typically used as benchmark to forecast sales volume and is the model that firm managers use when they are analyzing time-series data. In an univariate ARMA(p,q) model, y_t is assumed to be well described by the following equation:

$$\phi(L)(y_t - \hat{\mu}_y) = \theta(L)\varepsilon_t, \text{t=1,…,T},$$

where $\phi(L) = 1 - \phi_1 L - \ldots - \phi_p L^p$, $\theta(L) = 1 - \theta_1 L - \ldots - \theta_q L^q$ $\hat{\mu}_y$ is the sample average of y and ε_t is a white noise process with variance $\sigma_\varepsilon^{\ 2}$, i.e., $\varepsilon_t \overset{w.n.}{\sim} (0, \sigma_\varepsilon^{\ 2})$. Here, L denotes the lag operator, i.e., $L^j y_t = y_{t-j.}$ The roots of $\phi(z)$ are assumed to be outside the unit circle. The ARMA model was estimated by ordinary least squares (OLS) with no backcasting and White heteroskedasticity-consistent standard errors. The estimation was followed by a variety of diagnostic tests to ensure the adequacy of the estimated model.

The second estimated model is the TF model, which describes the relationship between an output variable (e.g., sales volume) and one or more explanatory variables. Suppose that y_t and x_t are second-order stationary processes, t = 1, …, T; then, the bivariate TF model can be written as:

$$\left(y_t - \hat{\mu}_y\right) = \frac{(\omega_0 + \omega_1 L + \omega_2 L^2 + \ldots + \omega_s L^s) L^b}{(1 + \delta_1 L + \delta_2 L^2 + \ldots + \delta_r L^r)} \left(x_t - \hat{\mu}_x\right) + n_t$$

$$\left(y_t - \hat{\mu}_y\right) = \frac{\omega(L) L^b}{\delta(L)} \left(x_t - \hat{\mu}_x\right) + \frac{\theta(L)}{\phi(L)} \varepsilon_t = v(L) \left(x_t - \hat{\mu}_x\right) + \frac{\theta(L)}{\phi(L)} \varepsilon_t$$

where b is a nonnegative integer called the transfer function time delay, ω(L) and δ(L) are polynomials in L of degree r and s, respectively, $\omega_0 \neq 0$, n_t is an ARMA(p, q) process with ϕ(L) and θ(L) defined as before with degree p and q, respectively, and $\varepsilon_t \overset{w.n.}{\sim} \left(0, \sigma_\varepsilon^{\ 2}\right)$. If all roots of the polynomial δ(L) lie outside the unit circle, then the transfer function can also be expressed in a linear form v(B). The other explanatory variables are added to the model with different functions ω and δ and a different time delay b.

The transfer function parameters are typically estimated by OLS with the delay parameter b fixed when the noise component n_t is uncorrelated with the explanatory variables x_t,. In our data, the explanatory variables, proposals and marketing, are endogenous because they are simultaneously determined by the output variable, sales volume, and hence, the OLS estimators are biased and inconsistent. To address this issue, the model was estimated by 2SLS.

To obtain consistent estimators for the TF model, we included an IV. The IV is an observed variable that satisfies two assumptions: it is uncorrelated with the error term but is correlated with the endogenous explanatory variable. The past values of time-series variables are selected as the IVs when stationary time series are analyzed. For example, proposals at time t are an endogenous explanatory variable in the sales volume equation at time t, and hence, we can use proposals at time t-1 as an instrument for proposals at time t.

Finally, the VAR model assumes that the group of endogenous variables (sales volume, proposals and marketing) composes a vector called **z**. Then, the VAR(p) model with one exogenous variable x can be written as:

$$\left(\mathbf{I} - \mathbf{\Phi}_1 L - \mathbf{\Phi}_2 L^2 - \ldots - \mathbf{\Phi}_p L^p\right)\left(\mathbf{z}_t - \hat{\boldsymbol{\mu}}_{\mathbf{z}}\right) = \boldsymbol{\beta} L^b \left(x_t - \hat{\mu}_x\right) + \boldsymbol{\varepsilon}_t$$

$$\mathbf{\Phi}(L)\left(\mathbf{z}_t - \hat{\boldsymbol{\mu}}_{\mathbf{z}}\right) = \boldsymbol{\beta} L^b \left(x_t - \hat{\mu}_x\right) + \boldsymbol{\varepsilon}_t,$$

where $\mathbf{\Phi}_i$ are (3x3) coefficient matrices, **β** is a (3x1) coefficient vector that measures the impact of x on **z** and $\boldsymbol{\varepsilon}_t$ is a trivariate white noise process with covariance matrix $\mathbf{\Sigma} = E\left(\boldsymbol{\varepsilon}_t \ \boldsymbol{\varepsilon}_t^{'}\right)$. The other exogenous variables are added to the model with different **β** coefficients and a different time delay b. Parameter estimation was performed by OLS, and the best VAR model was selected through consideration of the values of Akaike´s (AIC) and Schwarz´s (BIC) criteria. In our data, we estimated VARs of orders from 1 to 8 to account for short- and long-run business cycle effects. As the firm variables and economic variables are not cointegrated, the analysis was performed using the log transformations of stationary variables (sales volume, proposals, marketing and BNDES loans) and log first differences transformations of the other variables that have a unit root.

The BVAR model has the same form as the VAR model but differs with respect to the nature of the prior uncertainty assumed regarding the model's parameters—the prior density. We used the so-called natural conjugate (Normal-Wishart) family of prior densities and simulated draws of the relevant random variables through the use of the Monte Carlo methods presented in [31] and [32]. We selected the following values for the priori tightness: 0.1 for the overall prior, AR(1). intercept, sum of coefficient prior weight and drift prior and 0.07 for exogenous tightness. Other values were used, and the results were robust. We used the same procedure employed for the VAR model to select the best BVAR model.

IV. Forecasting accuracy

The model estimation used the 96 observations in the time window from January 2004 to December 2011. We used 4 additional observations from the year 2012 (Jan-Apr) to assess the out of sample forecasts. The sizes of our in and out of sample estimations were defined to guarantee the robust estimation of the models with 7 exogenous explanatory variables and two endogenous explanatory variables. We then compared the accuracy of the forecasts of the in-sample model using the in-sample observations and the out of sample observations.

The sample period includes the economic crisis that became evident months after the Lehman Brothers' bankruptcy in 2007. We then selected 21 months from November 2008 to July 2010 to analyze forecasting performance during the crisis period. Forecast errors may be higher during this period than during non-crisis periods. The volatility of sales volume increases during the crisis (see Figure 1). and hence, we expect to find an increase in forecasting errors during such a period. We used the correction procedure, described by [21] to obtain sales volume consistent estimators, as sales volume is log transformed and can under- or overestimate the expected value of sales owing to the exponentiated predicted values. We also considered the log returns of the following variables: reference rate, confidence index, stock market, exchange rate and FDI as well as the log of total BNDES loan volume. The log returns were used to obtain stationarity in the variables and to linearize the relations [2]. To simplify the explanation of the estimated models, the endogenous variables are defined as:

$$y_{1t} = \text{Log}(\text{Sales}_t) - \hat{\mu}_{\text{Log(Sales)}},$$
$$y_{2t} = \text{Log}(\text{Proposals}_t) - \hat{\mu}_{\text{Log(Proposals)}},$$
$$y_{3t} = \text{Log}(\text{Marketing}_t) - \hat{\mu}_{\text{Log(Marketing)}}.$$

ARMA model was estimated using the method proposed by Box and Jenkins, in which the ACF and PACF are used to identify the number of lags to be applied in the model. We estimated an ARMA(2,7) model, which only includes the parameter for MA with 7 lags, that is:

$$\left(1-\phi_1 L-\phi_2 L^2\right) y_t = \left(1-\theta_7 L^7\right)\varepsilon_t .$$

The ARMA(2,7) model was able to capture the autocorrelation structure of sales values, as the residuals were white noise.

Prior to estimating the TF, VAR and BVAR models, we analyzed the cross-correlograms of sales in relation to each exogenous variable. We used this procedure to select the number of lags for each variable. Each exogenous variable enters the model with only one lag, typically the larger cross-correlogram lag. We used the same dependent variable and lags for the exogenous variables in all 3 models to compare the forecast accuracy of the models. The lags that were used for the 7 exogenous variables are as follows: lag 6 for reference rate, lag 5 for confidence index, lag 1 for stock market, lag 2 for exchange rate, lag 3 for FDI, lag 1 for BNDES loan volume and lag 3 for PRI (a dummy variable for the BNDES loan program with reduced interest rates). The fitted model was:

$$y_{1t} = v_{02} y_{2t} + v_{03} y_{3t} + \sum_{j=1}^{7} v_j(L)\, x_{jt} + \frac{\left(1-\theta_7 L^7\right)}{\left(1-\phi_1 L-\phi_2 L^2\right)}\varepsilon_t .$$

In the TF model, the endogenous variables, proposals and marketing, needed to be included in the model with no lags. The 2SLSTF model was then selected to ensure the absence of bias and the consistency of the coefficient estimators. The residuals and squared residuals were checked, and the model showed adequate fit.

The VAR model used the same lags that were used for the TF model for the exogenous variables:

$$\left(\mathbf{I}-\mathbf{\Phi}_1 L-\mathbf{\Phi}_2 L^2-\ldots-\mathbf{\Phi}_p L^p\right)\mathbf{z}_t = \sum_{j=1}^{7}\boldsymbol{\beta}_j L^{b_j} x_{jt} + \boldsymbol{\varepsilon}_t \text{ , where } \mathbf{z}_t = \begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix}.$$

The BVAR model has the same form as the VAR model but with prior uncertainty assumed regarding the model's parameters. The best VAR and BVAR models were selected through consideration of the values of AIC and BIC, and in both cases, we selected the models with p equal to 1, i.e., the VAR(1) and BVAR(1) models. ACF and PACF are used as tools to assess models' suitability. The one-step-ahead forecasts results were evaluated according to three criteria used to compare forecasts: the RMSE, the MAE and the Absolute Percentage Error (MAPE) [33]. These measures are computed as follows:

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n}\left(y_t-\hat{y}_t\right)^2}{n}}, \quad MAE = \frac{1}{n}\sum_{t=1}^{n}\left|y_t-\hat{y}_t\right| \text{ and } MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{\left|y_t-\hat{y}_t\right|}{\left|y_t\right|},$$

where y_t *and* $\hat{y}_t$ are true sales volume and the one-step-ahead forecasting at time t and n is the number of forecasts. Assuming that the model holds during the post-sample period, we are particularly interested in the RMSE because this measure should reflect the forecasted standard deviations of the estimated model.

Table 3 presents the RMSE, MAE and MAPE of all the estimated models for the data set for the in sample (n=96) and out of sample periods (n=4). Table 3 shows the ARMA model's relative percentage RMSE to verify the forecast improvement of each model relative to the ARMA model (benchmark). The TF model has lower values for the three estimated forecasting errors and, hence, shows superior accuracy compared with all the other estimated models for the in and out of sample analysis. The 2SLSTF model outperforms all other models in the different samples of the time series. This result shows that accounting for endogeneity improves forecasting predictions. The 2SLSTF model increases the forecasting accuracy by 29% compared with the ARMA baseline model using out of sample data. Analyzing the in sample predictions reveals a 11% increase in accuracy. The 2SLSTF model also performs better in the out of sample compared with VAR and BVAR models with a reduction of up to 38% in the forecasting error compared with these models.

Table 3. RMSE, MAE and MAPE and a Comparison of the Forecasts Between the Estimated Models and the ARMA Model, Separated by Total in Sample, out of Crisis in Sample, in Crisis in Sample and out of Sample Periods

RMSE		**ARMA**	**TF-OLS**	**TF-2SLS**	**VAR1**	**BVAR1**
in sample	total	7977	7326	**7079**	7578	10008
	out crisis	7750	7595	**7555**	7847	10697
	in crisis	8722	6409	**5278**	6619	7390
out sample	total	3740	2848	**2649**	3593	3669
MAE						
in sample	total	6197	5346	**5081**	5424	7427
	out crisis	5930	5791	**5647**	5762	7955
	in crisis	7128	3946	**3272**	4311	5745
out sample	total	2697	2712	**2374**	3259	2642
MAPE						
in sample	total	42,51	27,91	**26,29**	28,38	36,69
	out crisis	31,66	26,17	**25,99**	28,02	33,54
	in crisis	80,21	33,37	**27,23**	29,58	46,74
out sample	total	31,03	28,71	**23,56**	35,91	24,25
ARMA Relative % RMSE						
in sample	total		8	**11**	5	-25
	out crisis		2	**3**	-1	-38
	in crisis		27	**39**	24	15
out sample	total		24	**29**	4	2

Note: The outperformed result for each line is shown in bold. ARMA Relative % RMSE = [1-(MODEL RMSE / ARMA RMSE)]*100. Out of sample reports n=4.

The multivariate models presented better forecasting performance when compared with the ARMA model, which was expected since such models take into account information from other variables in addition to the past sales. The MAPE results for the VAR model are similar to those for the 2SLSTF model for the forecasts within the sample; however, for the out of sample forecasts, the results for the 2SLSTF model are 31% more accurate than those for the VAR model. The BVAR model did not work as expected; we suspect that the choice of another prior could improve the model forecasts. To further test the accuracy of the 2SLSTF model, we also estimated all models for different out-of-sample sizes (n=8 and n=12). The 2SLSTF model consistently outperforms across all different out-of-sample sizes.

The analysis of the sample that includes the crisis period indicates that all models performed poorly with respect to the error measures compared with the analysis of other samples. This result demonstrates the difficulty of forecasting during the crisis period. In addition, the models that included economic exogenous variables, such as TF, VAR and BVAR, performed better than the baseline model. This result shows that including exogenous variables improves industrial sales forecasts during crisis periods. The 2SLSTF model has 39% greater accuracy than the ARMA model and is superior to the other estimated models.

Sales volatility increases during the crisis, from November 2008 to July 2010, with the highest levels observed in May and June 2009. This increase may affect the forecasts, increasing the forecast errors of the ARMA model. To analyze this further, we computed the linear correlation coefficient between volatility and the ARMA model's MAPE. The coefficient was equal to 0.39, indicating that moderate correlation exists between the two estimates and that the forecasts are less accurate during high volatility periods. We also computed the correlation between volatility and the 2SLSTF model's MAPE and obtained a coefficient of 0.09. Thus, the use of exogenous variables improves forecasts during crisis periods, suggesting that economic variables are the first variables that are affected during such periods.

V. Conclusions

Properly accounting for endogeneity has become a standard component of models in the economic literature. The application of established VAR and BVAR models is associated with problems related to misestimated coefficients and increased forecasting errors. Addressing these problems is particularly challenging in the context of industrial products, as a firm's management tends to directly influence several relevant variables. We expect that the simultaneous causal relationships among such variables affect forecast estimates. Therefore, accounting for endogenous and exogenous variables in forecast estimations and considering the appropriate model specification would increase the predictive accuracy of forecast models.

In this paper, we applied a two-stage least squares procedure to a transfer function following the econometric literature (e.g., [21]). Data from the records of an industrial product firm and public sources were used to test the accuracy of five forecasting models. We selected the variables and lags for each model through the use of correlograms and the ADF unit root test. To our knowledge, our paper is the first attempt in the empirical industrial context to address the problem of endogeneity. Our results reveal that the 2SLSTF model outperformed all other models estimated for industrial sales performance accounting for two endogenous independent variables: marketing and proposals. In the out of sample analysis, the 2SLSTF model was 38% more accurate, as assessed by the RMSE, than the baseline benchmark model (ARMA).

We also analyzed the models based on data from the 2008 global financial crisis, as previous research has called for additional investigation [17]. External events of such magnitude create severe problems for businesses' sales and influence forecasting models [5]. In analyzing a subsample from the postcrisis period, we found that the 2SLSTF model more accurately predicted sales. Compared with the baseline model, the 2SLSTF model was 39% more accurate. This result reinforces the importance of accounting for endogeneity in forecasting industrial product sales. Regardless of the type of firm data considered, our results suggest that accounting for the endogeneity of management variables is important whenever activity in the industrial product business is modeled.

REFERENCES

[1] Waddell, D. and Sohal, A. S., Forecasting: The Key to Managerial Decision Making, *Management Decision, 321*, 1994, 41-49.

[2] Touzani, S. and Van Buskirk, R., Estimating sales and sales market share from sales rank data for consumer appliances. *Physica A, 451*, 2016, 266–276.

[3] Kerkkänen, A., Korpela, J. and Huiskonnen, J., Demand Forecasting Errors in Industrial Context: Measurement and Impacts, *International Journal of Production Economics, 118,* 2009 43-48.

[4] Trapero, J. R., Pedregal, D. J., Fildes R. and Kourentzes, N., Analysis of Judgmental Adjustments in the Presence of Promotions, *International Journal of Forecasting*, *29*, 2013, 234–243.

[5] Qian, L. and Soopramanien, D., Using diffusion models to forecast market size in emerging markets with applications to the Chinese car market, *Journal of Business Research, 676*, 2014, 1226–1232.

[6] Ilmakunnas, P., Use of Macroeconomic Forecasts in Corporate Forecasting: a Note on Aggregation Problems, *International Journal of Forecasting, 12*, 1996, 383-388.

[7] Rippe, R., Wilkinson, M. and Morrison, D., Industrial Market Forecasting with Anticipations Data, *Management Science, 22*, 1976, 639-651.

[8] Lackman, C., Forecasting Sales for a B2B Product Category: Case of Auto Component Product, *Journal of Business and Industrial Marketing, 224*, 2007, 228-235.

[9] Reynolds, P. L. and Lancaster, G., Predictive strategic marketing management decisions in small firms: A possible Bayesian solution, *Management Decision, 456*, 2007, 1038-1057.

[10] Herbig, P., Milewicz, J. and Golden, J., The Do's and Don'ts of Sales Forecasting, *Industrial Marketing Management, 22*, 1993, 49-57.

[11] Byrne, T. M., Moon, M. and Mentzer, J., Motivating the industrial sales force in the sales forecasting process, *Industrial Marketing Management*, *40,* 2011, 128-138.

[12] Franses, P. H. and Legerstee, R., Do Statistical Forecasting Models for SKU-level Data Benefit from Including Past Expert Knowledge?, *International Journal of Forecasting*, *29*, 2013, 80–87.
[13] Kahn, K. B. and Mentzer, J. T., Forecasting in Consumer and Industrial Markets, *Journal of Business Forecasting*, *142*, 1995, 21-28.
[14] Rothe, J. T., Effectiveness of Sales Forecasting Methods, *Industrial Marketing Management*, *7*, 1978, 114-118.
[15] Walker, K. B. and Mcclelland, L., Management Forecasts and Statistical Prediction Model Forecasts in Corporate Budgeting, *Journal of Accounting Research*, *292*, 1991, 371-381.
[16] Danese, P. and Kalchschmidt, M., The role of the forecasting process in improving forecast accuracy and operational performance, *International Journal of Production Economics*, *131*, 2011, 204–214.
[17] Anderson, H.M. and Vahid, F., Forecasting the Volatility of Australian Stock Returns, *Journal of Business & Economic Statistics*, *251*, 2007, 76-90.
[18] Wright, D. J., Capon, G., Page, R., Quiroga, J., Taseen, A. A. and Tomasini, F., Evaluation of Forecasting Methods for Decision Support, *International Journal of Forecasting*, *2*, 1986, 139–153.
[19] Barton, H. H. and Nickerson, J. A., Correcting for Endogeneity in Strategic Management Research, *Strategic Organization*, *11*, 2003, 51-78.
[20] Jean, R-J. B., Deng, Z., Kim, D. and Yuan, X., Assessing endogeneity issues in international marketing research, *International Marketing Review*, *333*, 2016, 483-512.
[21] Wooldridge, J., *Introductory Econometrics: a Modern Approach* (South Western: Mason, 2009).
[22] Shaver, J. M., Accounting for Endogeneity When Assessing Strategy Performance: Does Entry Mode Choice Affect FDI Survival?, *Management Science*, *444*, 1998, 571-585.
[23] Bonhama. C., Gangnesa, B. and Zhoub. T., Modeling tourism: A fully identified VECM approach, *International Journal of Forecasting*, *25*, 2009, 531–549.
[24] Heckman, J. J. and Robb Jr., R., Alternative Methods for Evaluating the Impact of Interventions: An Overview, *Journal of Econometrics*, *30*, 1985, 239-267.
[25] Heckman, J. J., Sample Selection Bias as a Specification Error, *Econometrica*, *47*, 1979, 153-161.
[26] Stokes, H. H. and Neuburger, H., The Effect of Monetary Changes on Interest Rates: a Box-Jenkins Approach, *Review of Economics & Statistics*, *614*, 1979, 534.
[27] Angrist, J. D. and Imbens, G. W., Two-Stage Least Squares Estimation of Average Causal Effects in Models with Variable Treatment Intensity, *Journal of the American Statistical Association*, *90430*, 1995, 431-442.
[28] Theil, H., *Economic Forecasts and Policy* (North-Holland Publishing Co, Amsterdam, 1958)
[29] White, H., Instrumental Variables Estimation with Independent Observations, *Econometrica*, *50*, 1982, 482-499.
[30] Holland, P., Statistics and Causal Inference, *Journal of the American Statistical Association*, *81*, 1986, 945-970.
[31] Sims, C. A. and Zha, T. A., Bayesian Methods for Dynamic Multivariate Models, *International Economic Review*, *394*, 1998, 949–968.
[32] Waggoner, D. and Zha T. A., Conditional Forecasts in Dynamic Multivariate Models, working paper 98-22, Federal Reserve Bank of Atlanta, Atlanta, December, 1998.
[33] Diebold, F. X. and Mariano, R. S., Comparing Predictive Accuracy, *Journal of Business & Economic Statistics*, *13*, 1995, 253–263.