Forecasting industrial production via VAR and SARIMA with smart dummy

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Abstract

This article aims to find a statistical model that allows short-term forecast of the Brazilian industrial production. Two forecast models are proposed. The first is a SARIMA model with smart dummy. This dummy was built based on the predicted production index of the Brazilian Manufacturing Industry Survey (FGV/IBRE) aiming to capture abrupt falls in industrial production. The second model is a Combined VAR with 89 variables. These variables were joined in two antecedent indicators making the model estimation feasible. These indicators generated a Combined VAR model used to forecast a different month. Subsequently, the predicted values were seasonally adjusted taking into account the seasonal features of the Brazilian Bureau of Statistics. An out-of-sample analysis was done with predictions seasonally and not seasonally adjusted. Both models performance was satisfactory with a low prediction error, highlighting to the Combined VAR with prediction error under 2%.

Keywords: Industrial production, VAR models, SARIMA models, Brazilian Manufacturing Industry Survey (FGV/IBRE), Antecedent indicators

1. Introduction

The industrial production is a relevant economic variable used by the government and the market to make decisions. It's also a good GDP antecedent variable, which is released quarterly. In Brazil, the industrial production is released monthly but two months lagged. This lag increases the necessity to predict this variable at least two months ahead (present time).

A variety of techniques are used to forecast industrial production in literature. Madsen (1993), for instance, showed that the predicted production index, where the companies are asked about the expected production for the next months, were useful to forecast the industrial production 3 to 4 months ahead in the United Kingdom, Netherlands, Germany and France. Bodo et al. (2000)

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used ARIMA and VAR models to forecast the industrial production in the Euro Zone. The authors showed that ARIMA models generate reliable forecasts in the short term, however a bivariate VAR including industrial production from the states in each country generated better results than the ARIMA models. The authors also estimated a model using just variables from the four largest Euro Zone countries, but the over-parameterization problem arose.

In another article, Costantini (2013) used a factors model to forecast the industrial production in Italy. The forecasts were compared with the benchmark AR model, and the factors models gave better perfomance. Hassani et al. (2013) used the SSA (Singular Spectrum Analysis) technique to forecast the industrial production in the United Kingdom. The authors showed that the SSA had better performance than ARIMA models, and that the same technique, but multivariate (MSSA), had better performance than a VAR model. In 2009, Hassani et al. used econometric models to forecast monthly and quarterly macroeconomic variables. However, structural and time series models failed in accuracy for this kind of time series. This is because of technological changes, Governamental political changes and also consumer preferences. The authors also criticized some classical econometric model assumptions: for example, linearity and normality.

Heravi et al. (2004) compare the Artificial Neural Networks (ANNs) models and AR models forecast accuratly for the 24 industrial production time series from Europe. The authors state that AR models had better performance when analysing the short term forecasting while the ANNs models performed better for the time series signal. Heij et al. (2011) showed that the Conference Board's Composite Leading Index can be useful to forecast the industrial production in real time. When compared with the benchmark AR model, the model proposed by the authors presented lower forecast error.

As observed, there exist many ways to forecast the industrial production. The purpose of this article is to use Time Series models, such as (S)ARIMA and Vector Autoregressive models to forecast industrial production, while trying to control problems such as technological advances, changes in Government politics and consumer's preferences using smart dummies and building antecedent indicators. The SARIMA model was built with a dummy variable based on the predicted production index of the Brazilian Manufacturing Industry Survey (FGV/IBRE), which is able to capture abrupt changes in the industrial production. This is a simple idea but it was extremely useful to anticipate atypical movements in industrial production. Ozyildirim et al. (2010), Madsen (1993) and Simonassi et al. (2013) showed that predicted production indexes are useful to forecast industrial production.

Taking the second idea into account, many economic variables were used to explain the time series target. Due to the large number of variables available, we used the antecedent indicator technique to summarize the information and to make the model estimation feasible. This indicator is a result of the linear combination from many different time series and it is an antecedent indicator created for this purpose, that is, to anticipate the industrial production trajectory. This approach began with Burns & Mitchell (1946) and it is largely accepted and used nowadays. In Brazil, this technique was introduced by Contador (1977). Recent works can be found in Markwald et al. (1988); Chauvet (2001); Lima et al. (2006) and Morais (2013). Two antecedent variables were built. Each indicator generated one VAR model, which was used to forecast only one specific month. In truth, the two models put together make the forecasts two steps ahead.

Beyond this introduction, this article is organized in the following way: in the next section we explain the procedures to build the database and the new variables, the antecedent variables. Still in this section, we show the SARIMA and VAR models methodology and the parameters used by the Brazilian bureau of statistics to make the seasonal adjustment. Section 3 presents the model performance in and out of sample and a comparison between them. Ultimately, the final remarks and a discussion about future works are made in section 4, completing the article.

2. Proposed methodology

2.1. Database

The first step in building the database was to define the industrial production time span (January 2002 to Apr 2016 - 172 observations). It's important to highlight that the database has been available from IBGE since 1985, but, in 2002, the data were reformulated. This resulted in the discontinuation of the index.

Then, a variety of Brazilian economic time series (119) were collected. Further, 12 seasonal dummies and one variable to indicate the determinist trend of the industrial production were built. The time series unit wasn't homogeneous, for instance: monetary (R$, US$), volume, percentual variation (%) or index number. However, all the time series were transformed to an index number with fixed base in December 2001 = 100.

In short, all the time series variables, must have the following characteristics:

1. Periodicy: monthly;
2. Time span: Jan. 2002 to Apr.2016;
3. Unit: Fixed base index Dec. 2001 = 100 (except industrial production, dummies, trend, working days variables).

2.2. SARIMA model with smart dummy

The Box & Jenkins (1970) approach allows that future values can be forecast by using only present and past values. Such models are called Autoregressive Moving Average models or simply ARIMA. Taking into account seasonality, we have the SARIMA models.

When adjusting an ARIMA model for the industrial production index, it was noted that the residuals for the period of the economic crisis of 2008 (November and December) negatively influenced the model diagnosis and therefore this model needed to be reset. As a solution, a dummy variable based on another variable whose behaviour was sensitive to the occurrence of sharp falls in industrial production was built, and thus it would be possible to identify periods of crisis that negatively affect the forecast industrial production index in extreme cases.

To make this idea possible we used the predicted production index of the Brazilian Manufacturing Industry Survey (FGV/IBRE (2016)). This refers to the outlook for production in companies for three months ahead. The possible answers are: increase, neutral and decrease. The indicator is formulated to vary around 100 (neutral), and values above (below) that indicate optimism (pessimism). The predicted production index, instead of industrial production, is released in the current month. So, it's an antecendent variable from the target time series.

A period was defined as a crisis period (smart dummy equals 1), if in that month, the monthly variation of the predicted production index with seasonal adjustment was lower than the quantile 5% from the same variable taking into account the last 60 months (inclusive). In these periods the smart dummy is 1, in the others 0. The choice of the quantile and the number of months were chosen in order to reduce the forecast error two steps ahead. A total of 21 combinations were tested.

Before estimating the model the industrial production index stationarity was tested (Dickey & Fuller (1979)). The results indicate non-stationarity in level and stationarity after the first difference (Table 1).

Variable	**Equation**	**Selected Lag**	**Statistics τ**
IPI	no drift and no trend	24	-0.051
ΔIPI	no drift and no trend	14	-3.049

Table 1: Augmented Dickey-Fuller Test - Industrial Production Index (IPI)

Table 2 shows the estimated end model: a $\text{SARIMA}(3,1,0)(0,1,1)_{12}$ with smart dummy (D_1). The other dummy variable (D_2) represents the trend change after economic crisis. This last dummy assumes value 1 for the period after november 2008. All the parameters of the model are significant. It's important to highlight that the smart dummy reduced the MAPE, in crisis period, from 12.7% to 4.3%.

The functional form of the model is given by the equation (1). The residual diagnosis shows the model fitted well. There is no evidence of non normality (Jarque & Bera, 1980), linear autocorrelation (Ljung & Box, 1978) and heteroskedasticity.

$$(1+0.55L+0.26L^2-0.28L^3)\Delta\Delta^{12}\text{PIM}_t = (1+0.68L^{12})\varepsilon_t - 3.18\text{D}_{1t} - 13.77\text{D}_{2t} \quad (1)$$

Parameters	**Estimated values**	**Standard deviation**	***t* statistic**
AR1	-0.5522	0.0814	-6.7793***
AR2	-0.2570	0.0880	-2.9202***
AR3	0.2856	0.0773	3.6945***
SMA1	-0.6772	0.0812	-8.3424***
D_1	-3.1799	0.8845	-3.5951***
D_2	-13.7696	1.9222	-7.1634***

***: significance level 5%.

Table 2: SARIMA$(3,1,0)(0,1,1)_{12}$ model with smart dummy

2.3. Combined VAR with antecedent indicators

As other variables may be related to the interest variable and used to minimize the forecast error, we also estimated a multivariate VAR.

In general terms, considering a system with k variables with autoregressive order p, the VAR(p) model is given by:

$$y_t = A_0 + A_1 y_{t-1} + ... + A_p y_{t-p} + e_t \tag{2}$$

where:
y_t - column vector kx1 with k variables;
A_0 - column vector kx1 of intercept terms;
A_i - coeficient matrix kxk, $i = 1, ..., p$;
e_t - column vector kx1 of error terms.

In the equation (2) from the VAR(p) model it has k variables and p lags. The matrix A_0 has k parameters and each matrix A_i has k^2 parameters. Then, $k + pk^2$ needs to be estimated. It's clear the model is overparametrized. To make the estimation feasible, we have used the antecedent indicators technique to group the 132 variables. The antecedent indicators technique requires the choice of time series, isolated or combined, whose path anticipates the behavior of another time series. The chosen time series will be used as predictors of the target time series. All the steps of the antecedent indicators technique are presented in flow chart in the Figure 1.

Two antecedent indicators were built. To build the first indicator, denoted as IND_1, we considered, among the 132 time series, only those that were reported with a maximum of 1-month-lag. After that, a multiple linear regression model was adjusted with the dependent variable being the Industrial Production Index at time t and the covariates in $t-1$. The adjusted values from this regression are the IND_1.

The construction of the other indicator is given similarly. The IND_2 uses only those variables that are published with up to a 2-month-lag and in the linear regression model, the covariates are time $t-2$.

All the regression models were estimated using the *Stepwise* method with *backward* selection (Schwarz information criteria minimizaton). It's important

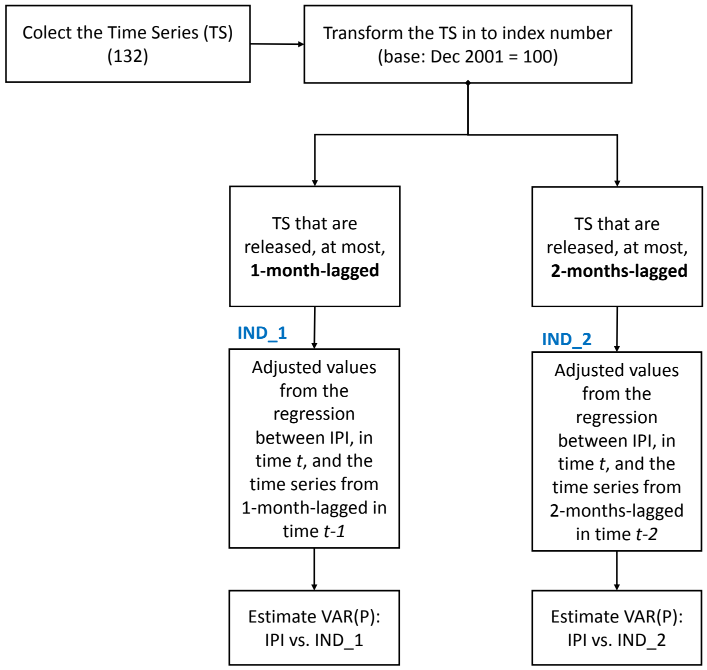

Figure 1: Estimating the antecedent indicators and the VAR models: a flow chart

to highlight that the use of linear regression to obtain the indicator variables was used by Markwald et al. (1988) and the method was satisfactory.

The antecedent indicators are, in fact, the adjusted values of the two linear regression models. The linear regression model was used in order to find the weights of the relation between industrial production, in present time, with other lagged variables. It's important to observe that the aim of this work is to minimize the forecast error and it's not concerned with the causality relation between industrial production and other variables, so the estimated coefficients (Table A1 - Appendix) should be analysed carefully.

The variables from model 1 aren't necessarily the same as in model 2 and, thus, it's possible to build an indicator with only the variables statistically significant to forecast the industrial production. As some variables from the initial database weren't used in any model, the covariates were reduced from 132 to 89 (Table A1 - Appendix).

After the construction of the indicators we estimated two bivariate VAR models. The first model was estimated only with industrial production and the IND_1. The second model was estimated with industrial production and the IND_2.

To estimate the VAR models the first step was to verify the unit root from the two antecedent indicators. The results available in Table 3 state that all the time series are integrated from order 1, with 95% confidence.

Indicator	**Test equation**	**selected lag**	**τ statistic**
IND_1	without constant and trend	24	0.0140
ΔIND_1	without constant and trend	14	-3.2545
IND_2	without constant and trend	14	-0.1701
ΔIND_2	without constant and trend	11	-2.9852

Table 3: Unit Root Test - Dickey and Fuller

As the time series are non stationary, the cointegration was verified. The results in Table 4 suggest, with 95% confidence, the cointegration relationship between IPI and the indicators IND_1 and IND_2. Therefore it's necessary to include the error correction vector in the equations of the models VAR. Following are the equations of the two VAR models with the error correction vector included.

Indicator	**Hypothesized No. of Cointegration Equations**	λ	λ_{max} **(test statistic)**	**Critical value (5%)**
IND_1	At most 1	0.1366	5.05	9.24
	None	0.0320	22.78	15.67
IND_2	At most 1	0.0147	4.69	9.24
	None	0.0299	24.59	15.67

Table 4: Johansen test for cointegration

- **VAR Model 1:** IPI vs. IND_1

$$\begin{aligned} \mathrm{IPI}_t = \ & 0.01 + 0.65\mathrm{IPI}_{t-1} - 0.10\mathrm{IPI}_{t-2} - 0.05\mathrm{IPI}_{t-3} - 0.06\mathrm{IPI}_{t-4} \\ & - 0.05\mathrm{IPI}_{t-5} - 0.02\mathrm{IPI}_{t-6} - 0.07\mathrm{IPI}_{t-7} + 0.02\mathrm{IPI}_{t-12} \\ & - 0.02\mathrm{IPI}_{t-13} + 0.98\mathrm{IND\_1}_t - 0.63\mathrm{IND\_1}_{t-1} + 0.10\mathrm{IND\_1}_{t-2} \\ & + 0.06\mathrm{IPI}_{t-3} + 0.05\mathrm{IND\_1}_{t-4} + 0.05\mathrm{IND\_1}_{t-5} + 0.02\mathrm{IND\_1}_{t-6} \\ & + 0.07\mathrm{IPI}_{t-7} \end{aligned} \tag{3}$$

- **VAR Model 2:** IPI vs. IND_2

$$\begin{aligned} \mathrm{IPI}_t = \ & -0.04 + 0.58\widehat{\mathrm{IPI}}_{t-1} - 0.10\mathrm{IPI}_{t-2} - 0.05\mathrm{IPI}_{t-3} - 0.05\mathrm{IPI}_{t-4} \\ & - 0.06\mathrm{IPI}_{t-5} + 1\mathrm{IND\_2}_t - 0.59\mathrm{IND\_2}_{t-1} + 0.10\mathrm{IND\_2}_{t-2} \\ & + 0.06\mathrm{IND\_2}_{t-3} + 0.04\mathrm{IND\_2}_{t-4} + 0.06\mathrm{IND\_2}_{t-5} \end{aligned} \tag{4}$$

The residuals analysis from the two models allows us to confirm that the models are suitable, since there is no evidence of the non-normality, autocorrelation and heteroskedasticity, with 95% confidence.

2.4. Seasonal Adjustment

The predicted values presented in this article were estimated taking into account the industrial production without seasonal adjustment. However, the predicted values with seasonal adjustment are extremely relevant for the economic analysis. Hence, after the forecast, the predicted values have been adjusted seasonally taking into account the features used by the official Brazilian Bureau of Statistics (IBGE), i.e. X12-ARIMA (an older version of the X-13ARIMA-SEATS(U.S. Census Bureau, 2013)) with the following configurations[1]:

- method: x11;
- regression variables: td, easter[1], carnaval;
- arima model: (0 1 1)(0 2 2);
- model span: Jan 2002 to Dec 2013;
- tranform function: log.

3. Results

The Figure 2 refers to the industrial production index time series. From 2002 to 2008 we can verify an increasing trend. At the end of 2008, we observed a strong decrease in the industrial production. From 2009 onwards the Brazilian industrial production returned to the same level before 2008 and has remained stable. The seasonal component is well defined: from January to October the industrial production is bigger than the average, in November and December it tends to be smaller.

Table 5 sums up the MAPE for the 3 estimated models. By analyzing the MAPE in-sample of the estimated models it is observed that the models provide good predictions one step ahead, highlighting the VAR models. However, the aim is to forecast two steps ahead. Then, a pseudo-out-of-sample analysis was also done for the period May/2014 to Apr/2016 (Table 6) aiming to evaluate the forecast performance two steps ahead. Each VAR is responsible for only one specific step ahead resulting in a combined VAR. In other words, the VAR model 1 will be responsible for forecasting the month immediately following the last observed IPI data; the VAR 2 model, using the VAR 1 model forecast, will be responsible for the second month immediately following the last IPI observed data. The Combined VAR forecast presents a forecast error considerably

[1] Methodological tutorials about seasonal adjustment of the industrial production are available at: http://www.ibge.gov.br/home/estatistica/indicadores/industria/pimpf/br/notas_metodologicas.shtm.

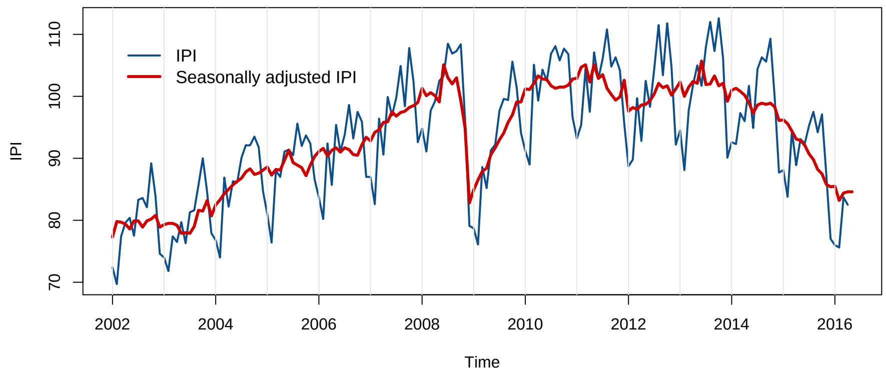

Figure 2: Brazilian Industrial Production index (Source: IBGE)

lower than the SARIMA model when the forecast during these two last years is evaluated.

	SARIMA	**VAR 1**	**VAR 2**
Not seasonally adjusted	1.85%	0.99%	0.78%
Seasonally adjusted	1.45%	0.88%	0.76%

Table 5: Mean Absolute Percentage Error (in-sample)

	SARIMA	**Combined VAR**
Not seasonally adjusted	2.71%	1.86%
Seasonally adjusted	2.38%	1.58%

Table 6: Mean Absolute Percentage Error (pseudo-out-of-sample)

The Figures 3 and 4 show, respectively, the IPI predicted values with and without seasonal adjustment from the SARIMA model and Combined VAR over the last two years (May 2014 to Apr 2016).

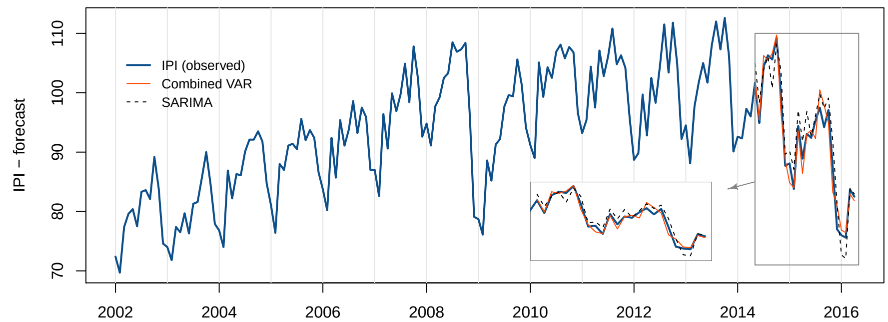

Figure 3: Previsão IPI sem ajuste sazonal via SARIMA e VAR Combinado

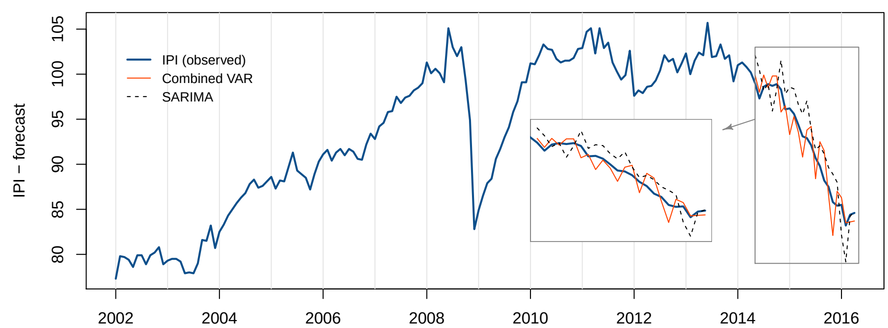

Figure 4: Previsão IPI com ajuste sazonal via SARIMA e VAR Combinado

4. Final Remarks

In the present work two models for predicting the Brazilian Industrial Production Index were developed. The first, an ARIMA model with a smart dummy to capture recession periods. The second model was a combined VAR in which various economic variables were used to explain the target series. Due to the large number of available economic variables, two leading indicators were used to summarize the information. Each leading indicator gave rise to a VAR model, which was used for the prediction of only one particular month.

The forecast results were satisfactory with a low mean absolute percentage error (around 2%), highlighting the Combined VAR, which used 89 economic variables in its forecast, with performance better than the SARIMA model with

Smart dummy.

Our future work: we intend to simulate diverse scenarios to evaluate the performance of models in situations where there were abrupt changes in the economy and to study other methods of aggregation of time series for the development of leading indicators, for example, major components and factor analysis.

References

Bodo, G., Golinelli, R., & Parigi, G. (2000). Forecasting industrial production in the euro area. *Empirical Economics*, *25*(4), 541–561.

Box, G. E. P., & Jenkins, G. M. (1970). *Time Series Analysis forecasting and control*. San Francisco: Holden Day.

Burns, A. F., & Mitchell, W. C. (1946). *Measuring Business Cycles*. NBER. URL http://www.nber.org/books/burn46-1

Chauvet, M. (2001). Indicadores antecedentes da inflação. *Pesquisa e Planejamento Econômico*.

Contador, C. (1977). Ciclos econômicos e indicadores de atividade. *Pesquisa e Planejamento Econômico*.

Costantini, M. (2013). Forecasting the industrial production using alternative factor models and business survey data. *Journal of Applied Statistics*, *40*(10), 2275–2289.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American Statistical Association*, *74*(366), 427–431.

FGV/IBRE (2016). Fundação Getúlio Vargas - Instituto Brasileiro de Economia. Sondagens e Índices de Confiança. URL http://portalibre.fgv.br/main.jsp?lumChannelId=402880811D8E34B9011D92BA032B198D

Hassani, H., Heravi, S., & Zhigljavsky, A. (2009). Forecasting european industrial production with singular spectrum analysis. *International Journal of Forecasting*, *25*(1), 103–118.

Hassani, H., Heravi, S., & Zhigljavsky, A. (2013). Forecasting uk industrial production with multivariate singular spectrum analysis. *Journal of Forecasting*, *32*(5), 395–408.

Heij, C., van Dijk, D., & Groenen, P. J. (2011). Real-time macroeconomic forecasting with leading indicators: An empirical comparison. *International Journal of Forecasting*, *27*(2), 466 – 481. URL http://www.sciencedirect.com/science/article/pii/S0169207010001056

Heravi, S., Osborn, D. R., & Birchenhall, C. (2004). Linear versus neural network forecasts for european industrial production series. *International Journal of Forecasting*, *20*(3), 435 – 446.
URL http://www.sciencedirect.com/science/article/pii/S0169207003000621

Jarque, C. M., & Bera, A. K. (1980). Efficient tests for normality, homoscedasticity and serial independence of regression residuals. *Economics Letters*, *6*(3), 255–259.
URL http://www.sciencedirect.com/science/article/pii/0165176580900245

Lima, I. C., Moro, S., & Junior, F. G. (2006). Ciclos e previsão cíclica: Um modelo de indicadores antecedentes para a economia brasileira. *ANPEC*.

Ljung, G. M., & Box, G. E. P. (1978). On a measure of a lack of fit in time series models. *Biometrika*, *65*(2), 297–303.

Madsen, J. B. (1993). The predictive value of production expectations in manufacturing industry. *Journal of Forecasting*, *12*(3-4), 273–289.

Markwald, R., Moreira, A. R., & Pereira, P. L. (1988). Previsão do nível e ciclo da produção industrial. *Instituto de Planejamento Econômico e Social*.

Morais, I. A. (2013). Ciclo e indicadores antecedentes na indústria do rio grande do sul. *Nova Economia*.

Ozyildirim, A., Schaitkin, B., & Zarnowitz, V. (2010). Business cycles in the euro area defined with coincident economic indicators and predicted with leading economic indicators. *Journal of Forecasting*, *29*(1-2), 6–28.

Simonassi, A. F., de Albuquerque e Arraes, R., & de Oliveira, D. X. A. (2013). The role of expectations in modeling and forecasting industrial production. *Revista Brasileira de Economia de Empresas*, *13*(2).

U.S. Census Bureau (2013). The X-13ARIMA-SEATS Seasonal Adjustment Program.
URL https://www.census.gov/srd/www/x13as/

Appendix

Table A1: Time series and coefficients used to estimate the two antecedent indicators

Name (Source)	**IND_1**	**IND_2**
Constant	258.75	54.37
January dummy variable	-6.23	11.10
February dummy variable		13.42
March dummy variable		22.41
April dummy variable	2.85	20.30
May dummy variable		24.29
June dummy variable	2.27	25.67
July dummy variable	7.02	26.49
August dummy variable	5.45	32.70
September dummy variable	9.43	24.02
October dummy variable	8.47	16.33
November dummy variable		12.01
Trend		-0.96
Production - Automobile (ANFAVEA)		13×10^{-3}
Cars and light commercial vehicles production (ANFAVEA)		-13×10^{-3}
Production - Truck - units (ANFAVEA)		-17×10^{-3}
Crawler bulldozer production - unidades (ANFAVEA)	-0.01	-49×10^{-3}
Harvesters production - unidades (ANFAVEA)		-19×10^{-3}
Backhoes roduction - unidades (ANFAVEA)	-76×10^{-3}	-23×10^{-3}
Other agricultural machines production - unit (ANFAVEA)	0.01	
Oil products consumption - Gasoline - barrels/day (thousand) (ANP)		0.07
Oil products consumption - GLP - barrels/day (thousand) (ANP)		0.05
Worked hours - production - industry - index (average 2006 = 100) - SP (FIESP)		-0.36
Capacity utilization - industry - SP - (%) (FIESP)		-0.29
Petroleum products consumption - diesel oil - barrels/day (thousand) (ANP)		-0.02
Petroleum products consumption - Total - barrels/day (thousand) (ANP)		-0.01
Eletricity consumption - Brazil - Commerce - GWh (ELETROBRAS)		-0.01
Eletricity consumption - Brazil - Industry - GWh (ELETROBRAS)		-0.05
Eletricity consumption - Brazil - Other - GWh (ELETROBRAS)		-0.01
Eletricity consumption - Brazil - Total - GWh (ELETROBRAS)		6×10^{-3}
Eletricity consumption - Brazil - North - Industrial - GWh (ELETROBRAS)		0.04
Eletricity consumption - Brazil - Northeast - Industrial - GWh (ELETROBRAS)		0.04
Eletricity consumption - Brazil - South - Industrial - GWh (ELETROBRAS)		0.04
Eletricity consumption - Brazil - Southeast - Industrial - GWh (ELETROBRAS)		0.04
Formal employment - Manufacturing Industry (total) (MTE)		0.81

Formal employment - Industrial services of public utility - index (MTE)		-0.84
Exports - manufactured products - US$ (MDIC/Secex)		7.74×10^{-10}
Exports- Gasoline - US$ (MDIC/Secex)		-9.17×10^{-9}
Exports - Paper and paperboard for writing, printing or graphic purposes - US$ (MDIC/Secex)		8.13×10^{-8}
Exports - Laminate products of iron or steel - US$ (MDIC/Secex)		1.77×10^{-8}
Imports - Durable goods - US$ (MDIC/Secex)		-1.07×10^{-8}
Imports - Non-durable goods - US$ (MDIC/Secex)	7.44×10^{-9}	
Imports - Parts and pieces for capital goods - industry - kg (MDIC/Secex)		1.11×10^{-7}
Interest rate - Selic (annualized) (BCB)		-0.13
Ibovespa - Monthly percentage change - % (BM&FBOVESPA)	0.02	0.04
Automobile sales - domestic market - unit (ANFAVEA)	8.24×10^{-5}	
Motorcycle Sales - unit (ANFAVEA)		3.12×10^{-5}
Actual sales - industry - index (average 2006 = 100) - SP (FIESP)		0.08
National Consumer Price Index (INPC) (IBGE)	1.73	1.75
National Broad Consumer Price Index (INPC) (IBGE)	-3.22	-2.78
Vehicles sales - Automobile - Units (FENABRAVE)	-4×10^{-4}	-7×10^{-4}
Vehicles sales - Comerciais leves - Units (FENABRAVE)		-6×10^{-4}
Vehicles sales - Truck - Units (FENABRAVE)	-9×10^{-4}	
Vehicles sales - Bus - Units (FENABRAVE)	-14×10^{-3}	
Vehicles sales - Total - Units (FENABRAVE)	4×10^{-4}	6×10^{-4}
INCC-DI - Labor (FGV/IBRE)	0.16	0.14
Market General Price Index (IGP-M) - Monthly percentage change - % (FGV/IBRE)	-1.55	0.88
Wholesale Price Index (IPA) - ORIGIN - DI (FGV/IBRE)	0.53	
IPA - Agricultural Products - ORIGIN - DI (FGV/IBRE)	-0.06	-0.04
IPA - Mineral Coal - ORIGIN - DI (FGV/IBRE)	0.07	
IPA - Food & Beverage Products - ORIGIN - DI (FGV/IBRE)	-0.11	
IPA - Wood products - ORIGIN - DI (FGV/IBRE)		0.18
IPA - Cellulose, Paper and Paper Products - ORIGIN - DI (FGV/IBRE)	-0.36	-0.48
IPA - Oil and Alcohol Products - ORIGIN - DI (FGV/IBRE)	-0.10	0.08
IPA - Chemicals - ORIGIN - DI (FGV/IBRE)		-0.13
IPA - Rubber items and Plastic Material - ORIGIN - DI (FGV/IBRE)		-0.12
IPA - Machines and Equipment - ORIGIN - DI (FGV/IBRE)		-0.23
IPA - Computer hardware - ORIGIN - DI (FGV/IBRE)	-0.09	
IPA - Electronic materials, devices and communication equipment - ORIGIN - DI (FGV/IBRE)	0.08	0.12
IPA - Furniture and securities items - ORIGIN - DI (FGV/IBRE)		0.37
IPA - Non-ferrous minerals - ORIGIN - DI (FGV/IBRE)		0.02
IPA - Paper or cardboard package - ORIGIN - DI (FGV/IBRE)	0.10	0.22
IPA - Stones and sands - ORIGIN - DI (FGV/IBRE)	-0.11	-0.13
IPA - Cellulose - ORIGIN - DI (FGV/IBRE)	0.08	0.07
IPC - Food - BR - DI (FGV/IBRE)	0.22	
IPC - Transport - BR - DI (FGV/IBRE)	0.25	0.09

ABCR Index - Weights	-0.18	
Total Demand (FGV/IBRE)	-2.18	2.99
Domestic Demand (FGV/IBRE)	-0.30	
External Demand (FGV/IBRE)		-0.03
Inventory Level (FGV/IBRE)	-2.24	2.68
Current Situation of Business (FGV/IBRE)	-2.36	2.61
Expected Total Demand (FGV/IBRE)	-0.20	
Expected Domestic Demand (FGV/IBRE)	0.28	
Expected Production (FGV/IBRE)	-1.87	
Expected Employment (FGV/IBRE)	-1.81	0.14
Business trend (FGV/IBRE)	-1.88	
Industry Confidence Index (FGV/IBRE)		-4.02
Current Situation Index (FGV/IBRE)	6.81	-5.83
Expectations Index (IE) (FGV/IBRE)	5.28	1.88
Boxes, accessories and sheet Expedition - corrugated cardboard - quantity - Tonne (ABPO)	-3.54×10^{-5}	