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The dynamics of Brazilian Industrial Production in periods of growth and the covid-19 pandemic crisis using the Markov Switching model

Carlos Alberto Gonçalves da Silva
Visiting Researcher at the Postgraduate Program in Economics Sciences (PPGCE) - State University of Rio de Janeiro (UERJ), Rio de Janeiro, Brazil.

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ABSTRACT: This article uses the Markov Switching Dynamic Regression (MS-DR) model, in order to verify the dynamics of industrial production in Brazil during the period from January 2002 to December 2020, in which the subprime crisis and the crisis of the COVID-19. In particular, two regimes were used (regime 1 - growth and regime 2 - recession or retraction). Regime 1 is more persistent, that is, the probability of staying in that regime in a later period is 97,66% and the change to regime 2 is 31,79%. In regime 2, the probability of maintaining this regime in the period t + 1 is 68,21%, while the probability of changing to regime 1 is 2,34%.

Keywords: Markov Switching Dynamic Regression, Covid-19 Pandemic, Brazilian Industrial production

I. INTRODUCTION

The econometric works on the estimation of regressions subject to regime changes that follow a Markov chain were developed by Quandt (1972), Goldfeld and Quandt (1973). Hamilton (1989) made important advances in the method developed by Goldfeld and Quandt (1973), by specifying that changes in regimes follow an auto-regressive process. In this sense, he developed a non-linear and smoothed estimation algorithm to find the high and low regimes of the economic series, seeking to maximize the likelihood function in relation to the parameters estimated in the model. This methodology allowed statistical inferences to be made about the different regimes not observed in the series. The model endogenously estimates the dates of the structural changes in the series. Hamilton (1989) applied the method to investigate the nonlinear behavior of the growth of the United States economy and the results showed that the model can be used as an important tool for measuring business cycles.

Hamilton and Susmel (1994) use a model with changes, with respect to volatility. According to the authors, the regime change model, applied to the returns of the American stock market, fits the data better than the ARCH models without regime change.

Ang and Bekaert (2002) applied using a non-linear model to interest rates in the USA, Germany and the United Kingdom. Thus, the authors showed that interest rate regimes correspond reasonably well with US economic cycles, being extremely important to study the effects of monetary policy shocks on the economy.

Ismail and Isa (2006) used regime change testing in their study to detect non-linear characteristics in the exchange rates of three Asian countries. They found that the null hypothesis of linearity is rejected and there is evidence of structural breaks in the exchange rate series.

Júnior and Zuanazzi (2014) tested the hypothesis of non-linearity of the sensitivity of the return on assets of companies from Rio Grande do Sul under different Markovian risk regimes: periods of crisis and stability. They considered three assets of Rio Grande do Sul companies tradable on the São Paulo Stock Exchange (Bovespa). The results showed that the non-linear model (MS-CAPM) is the most suitable. In addition, evidence that assets are more susceptible to macroeconomic changes in times of crisis than in periods of stability.

Mahjoub and Chaskmi (2019) applied the Markov Switching model with two regimes, to identify periods of speculative bubble formation and explosion in the Iranian capital market. Regimen 1 is bubble growth and the explosion stage and regime 2 identifies bubble loss. The result of the research shows that the stock index of the Iranian capital market in the analyzed period

Panda et al. (2017) examine the changing behavior of the dynamic Markov regime between the spot and the futures market in relation to interest rates in India. The study uses daily data on volumes, weighted average price, weighted average yield for the spot market and total values, open interest, settlement price from January 21, 2014 to October 30, 2014. All data come from Clearing Corporation of India Ltd. (CCIL) and the National Stock Exchange (NSE). The authors used regime change regression to capture the behavior of changes, as well as the estimated probability and estimated duration of each regime.

Peira and Soledad (2002) implemented a regime change framework to study speculative attacks against EMS currencies during 1979–1993. To identify speculative episodes, we model exchange rates, reserves and interest rates as time series subject to discrete regime changes between two possible states: "quiet" and "speculative". We allow the odds of switching between states to be a function of fundamentals and expectations. The regime change framework improves the ability to identify speculative attacks vis-à-vis the speculative pressure indices used in the literature. The results also indicate that fundamentals (mainly budget deficits) and expectations drive the likelihood of moving to a speculative state.

Ozdemir (2020) in his study is to assess the feed price driven dynamics of the U.S. wholesale beef prices in which regime switches are induced by transitions between Markov regimes. By allowing the transition probabilities to vary according to some main grain feed prices, we examine if the regime transition probabilities vary over time under two different states of the growth rate of beef prices as “low-mean growth” and “high-mean growth” price regimes. The results show that when the prices are in high-mean growth regime, the probability that it will remain in this regime is greater than that it will switch to low-mean regime. This findings also indicate that livestock feed prices provides some predicted power to the model of beef price regime switching process and supports livestock feed prices contributing to whether the beef price levels remains in low/high-mean regime. By employing Markov switching dynamic regression model, we also find that all types of the feed prices have a significant effect on the beef prices in low-growth regime, but only the prices of hay and sorghum significantly affect the beef prices in the high-growth regime.

Xaba et al. (2019) used a Markov-switching dynamic regression (MS-DR) model to estimate appropriate models for BRICS countries. The preliminary analysis was done using data from 01/1997 to 01/2017 and to study the movement of 5 stock market returns series. The study further determined if stock market returns exhibit nonlinear relationship or not. The purpose of the study is to measure the switch in returns between two regimes for the five stock market returns, and, secondly, to measure the duration of each regime for all the stock market returns under examination. The results proved the MS-DR model to be useful, with the best fit, to evaluate the characteristics of BRICS countries.

Choi and Hammoudeh (2010) use the Markov Switching model with two volatility regimes for the strategic commodity prices of Brent oil, WTI oil, copper, gold and silver, and the S&P 500 index, but with varying high-to-low volatility ratios. The dynamic conditional correlations (DCCs) indicate increasing correlations among all the commodities since the 2003 Iraq war but decreasing correlations with the S&P 500 index. The commodities also show different volatility persistence responses to financial and geopolitical crises, while the S&P 500 index responds to both financial and geopolitical crises.

Moolman (2004) found that Linear models are incapable of capturing business cycle asymmetries. This has recently spurred interest in non-linear models such as the Markov switching regime (MS) technique of modelling business cycles. The MS model can distinguish business cycle recession and expansion phases, and is sufficiently flexible to allow different relationships to apply over these phases. In this study, the South African business cycle is modelled using a MS model. This technique can be used to simultaneously estimate the data generating process of real GDP growth and classify each observation into one of two regimes (i.e. low-growth and high-growth regimes).

Bismans and Roux (2013) use Markov-switching dynamic regression model to the real quarterly GDP time series from 1981 to 2010 in order to detect turning points in the South African business cycle. The model consists of several explicative variables. These include short and long term interest rates, monetary aggregates as well as the difference between long and short term interest rates.

This article makes a quantitative analysis using the Markov Switching Dynamic Regression (MS-DR) model, with the objective of verifying the dynamics of industrial production in Brazil, covering the period from January 2002 to December 2020, when the subprime crisis and the COVID-19 crisis. In particular, two regimes are used (regime 1 - growth and regime 2 - recession or contraction).

II. METHODOLOGY AND DATA

Markov Switching Dynamic Regression Model

Hamilton (1989) proposed MS that is based on the assumption that the development of X_t can be explained by states (or regimes), where a two regime Markov-switching regression model can be expressed as:

Regime 1: $Y_t = \mu_1 + \varphi Y_{t-1} + \varepsilon_t$

Regime 2 : $Y_t = \mu_2 + \varphi Y_{t-1} + \varepsilon_t$

where Y_t is the dependent variable,

μ_1 and μ_2 are the intercepts in each state (regime),

φ is the autoregressive coefficient and ε_t is the error at time t.

In the case where the state (regime) shifts are known, the two regime Markov-switching model can expressed as:

$$Y_t = S_t\mu_1 + (1 - S_t)\mu_2 + \varphi Y_{t-1} + \varepsilon_t$$

where S_t represents the regime and is equal to 1 if the process is in regime 1 and 2 if it is in regime 2. However, in most cases it is not possible to observe in which regime S_t the process is currently in and therefore unknown. In Markov-switching regression models the regime S_t follows a Markov chain. A model with k regime-dependent intercepts, can be expressed as:

$$Y_t = S_t\mu_{st} + \varphi Y_{t-1} + \varepsilon_t$$

Where $\mu_{st} = \mu_1, \mu_2, ... , \mu_k$ for $S_t = 1,2,......., k$ regimes.

The transition of probabilities between the regimes is carried out by a first order Markov process as follows:

$$\rho_{ij} = \Pr(S_t = j)|s_{t-1} = i)$$

On what ρ_{ij} refers to the probability of being on the regime j given that the process is in the regime i, where $\sum_{i=1}^{N} \rho_{ij} = 1$ for all $i, j \in (1,2,.....N)$.

The transition probabilities in a square matrix of order N, known as the transition matrix and denoted by P, have the following form:

$$P = \begin{bmatrix} \rho_{11} & \rho_{12} \\ \rho_{21} & \rho_{22} \end{bmatrix}$$

where

$$\rho_{11} = P[s_t = 1; s_{t+1} = 1]$$
$$\rho_{12} = P[s_t = 2; s_{t+1} = 1]$$
$$\rho_{21} = P[s_t = 1; s_{t+1} = 2]$$
$$\rho_{22} = P[s = 2; s_{t+1} = 2]$$
$$\rho_{11} + \rho_{12} = 1 \quad \text{e} \quad \rho_{21} + \rho_{22} = 1$$

Thus, it is assumed that the transition matrix is irreducible and unconditional (if one of the values of the transition matrix is equal to the unit and all other eigenvalues are within the unit circle). With these conditions, there is a stationary probability distribution of the regimes (Krolzig, 1997). Unconditional probabilities can be determined as follows:

$$\rho_1 = (1 - \rho_{11})/(2 - \rho_{11} - \rho_{22})$$
$$\rho_2 = (1 - \rho_{22})/(2 - \rho_{11} - \rho_{22})$$

The probability of being in regime 1 in equilibrium is obtained by ρ_1 and the probability of being in regime 2 is determined by ρ_2.

In the view of Doornik (2013) the Markov-switching models can be MS-AR (Markov-switching autoregression) and MS-DR (Markov-switching dynamic regression). The first is characterized by a more gradual adjustment, appropriate to the most stable series, whose autoregressive component is formed by the difference between the lagged endogenous variable and the average estimated for the endogenous variable in the S_{t-1} regime; and the second adjusts immediately to the new regime, with a more accentuated transition, since the autoregressive component covers only the endogenous variable.

In the present article, the series data are monthly, which chose to use the MS-DR model as an estimation method to identify regime changes, the number of periods, the duration and the probability of transition from one regime to another.

The MS-DR model can be specified as:

$$y_t = v(S_t) + \alpha y_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim N[0, \sigma^2]$$

Doornik (2013) adds that the MS-DR model with a structural component is important for analyzing time series that present alternations of values in the mean and variance. In this paper, the MS-DR is estimated with two regimes, which represent expansion and recession periods.

The maximum likelihood estimator is used to determine the parameters of the MS-DR. Therefore, the probability function of the model log with two regimes is expressed as follows:

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$$\ln L = \sum_{t=1}^{T} \ln \left\{ \sum_{j=1}^{2} f(y_t \mid S_t, y_{t-1}) \Pr(S_t = j \mid Y_{t-1}) \right\}$$

Where the term $\Pr(S_t = j \mid Y_{t-1})$ is the probability of being in each regime. Given away $\Pr(S_{t-1} = i \mid Y_{t-1})$, i = 1,2.

Finally, from the transition matrix it determines the expected duration of each regime. The closer the probability is to one, the longer it takes to switch from another regime. Thus the expected duration can be expressed as:

$$Expected \quad duration(D_i) = \frac{1}{1-\rho_{ij}}$$

The duration time in each of the two regimes can be determined as:

$$D_1 = 1/(1-\rho_{11}) \qquad D_2 = 1/(1-\rho_{22})$$

Linearity Test (BDS)

Once it is detected that the distribution is not normal, it is necessary to test the model for linearity. This test was developed by Brock, Dechert, and Scheinkman (1987) used to test if the random variables that compose a series are independent and identically distributed (IID), that is, it can verify several situations in which the variables are not IID, such as non-stationarity, nonlinearity and deterministic chaos. The test is based on the concept of spatial correlation of chaos theory and according to the authors the BDS statistic is formulated through the Equation:

$$W_m^n(\varepsilon) = \frac{\sqrt{N}\,(C_m^n(\varepsilon) - (C_1^n(\varepsilon))^m}{\sigma_m(\varepsilon)}$$

Where $W_m^n(\varepsilon)$ it converges to a normal distribution N (0, 1) as n tends to infinity.
Thus, hypothesis tests are:

H_0: the series follows an iid (independent and identically distributed) process.

H_1: the series does not follow an iid (independent and identically distributed) process.

Data

The data used in this study refer to monthly industrial production, covering the period from January 2002 to December 2020, in a total of 228 monthly observations. The data were obtained from the ipeadata website.

III. EMPIRICAL RESULTS

Preliminary Analysis

The daily returns were calculated using the formula: $r_t = \ln(P_t) - \ln(P_{t-1})$. This P_t represents the number of points at closing on day t and P_{t-1} the number of points at closing on the previous day (t-1). Figures 1 and 2 show the behavior of the industrial production daily quotation and return series in the period considered.

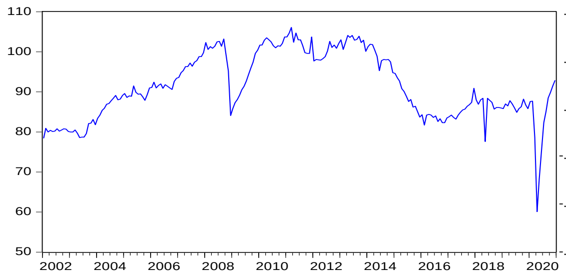

Figure 1. Monthly industrial production

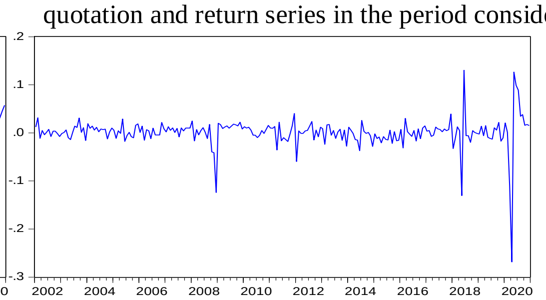

Figure 2. Monthly returns on industrial production

In the visual inspection of Figure 2, within the analysis period, there is a marked volatility in returns. Thus, it was necessary to test the normality and stationarity of the series of returns from industrial production for application of the MS-DR model.

Some basic descriptive statistics are presented in Table 1. It can be observed that the monthly returns of the industrial production present a leptocurtic distribution due to the excess of kurtosis (33,05852) in relation to the normal distribution (3.0), that is, it has heavier tail. It is also verified that the series is negatively asymmetrical. The analysis of the results shows that both the mean (0,001070) and the median (0,004228) presented values close to zero. The variation between the minimum value (-0,268362) and the maximum value (0.130305) shown by the series can be explained due to some significant oscillations in the index returns. The low value of the standard deviation (0.030754) indicates that, in general, the high variations in the series occurred in a few occasions, that is, in periods of positive and negative peaks. The statistics of Jarque - Bera

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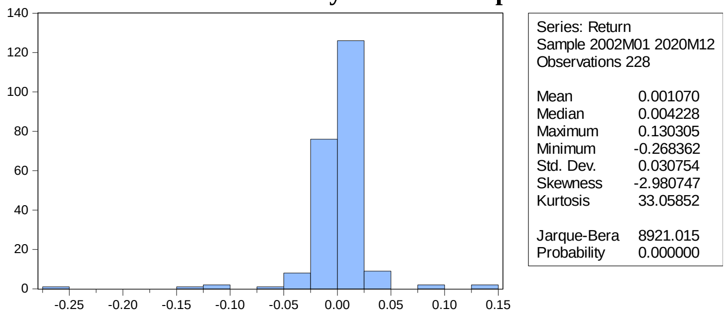
(1987) indicated the rejection of the normality of the distribution of the series, with p-value equal to zero.

Table 1. Statistical summary of industrial production returns



Source: E-views 9.0.

The Q-Q Plot represents one of the most used graphic methods to verify the normality of time series. The procedure used consists of graphically comparing the theoretical amounts of the normal distribution with the amounts of the sample data. Figure 3 shows a non-linear relationship between the theoretical and empirical quantiles, which is quite pronounced in the tails of the distributions, indicating heavier tails in the empirical distribution. Therefore, all tests rejected the hypothesis of normality of the analyzed series.

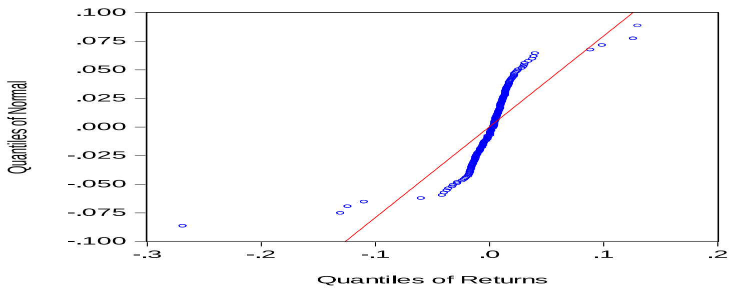


Figure 3. Plot Q-Q of industrial production returns.

The Dickey and Fuller (1981); Phillips and Perron (1988); tests and Kwiatkowski, Phillips, Schmidt, and Shin (1992) tests with constant and trend, identified that the series of industrial production returns are stationary and do not contain unit roots, as presented in Table 2

Table 2. Stationary test for industrial production returns .

Variable	ADF	Critical value (5%)	PP	Critical value (5%)	KPSS	Critical value (5%)
Industrial Production	-14,6643	-3,4297	-15,0690	-3,4297	0,0583	0,1460

Souce: E-views 9.0.

Before the estimation of the Markov Switching Dynamic Regression (MS-DR) model, a nonlinearity test may be necessary to describe the characteristics of the historical series of the industrial production returns. Thus, in Table 3 shows that the results presented indicate the nonlinearity effect, that is, that the probabilities are less than 5% at the significance level, implying a rejection of the null hypothesis that the returns series is linearly dependent.

Table-3. Test to the time independence of the industrial production (BDS)

Dimension	BDS Statistics	Statistics Z	Probability
2	0,0480	7,0335	0,0000
3	0,0763	7,0132	0,0000
4	0,0865	6,6486	0,0000
5	0,0819	6,0196	0,0000
6	0,0759	5,7619	0,0000

Source: Prepared by the author based on the research.

Markov-switching dynamic regression (MS-DR) model

Table 4 presents estimates of the model using the maximum likelihood method, using the OxMetrics 6.0 software (PcGive14). The adjusted model refers to the MS (2) -DR, variation of the mean and variance according to the regime (state). It is observed that all parameters are significant. The regime (1) expresses a positive average growth in industrial production. In regime (2), it presents a negative average result, that is, a retraction in industrial production. In regime 1, the estimated average monthly growth is 0,22% with a variance of 0,013. Regimen 2 identifies a negative monthly growth of -1,38% with a variance of 0,104.

Portmanteau indicate that there is no presence of autocorrelation of residues. The results of the ARCH-LM tests suggest the acceptance of the model homoscedasticity hypothesis. As for the normality tests Jarque-Bera (1987) does not reject the hypothesis of normality. Thus, the model presents a positive diagnosis and an adequate adjustment demonstrated in the results of the various tests carried out in the present study.

In the transaction and persistence matrix of the regimes, it appears that the current regime 1 is more persistent, that is, the probability of remaining in this regime in a later period is approximately 97,66%, and that of changing to regime 2 is on the order of 31,79%. In regime 2 the probability of continuing in this regime in the period t + 1 is 68,21%, while the probability of switching to regime 1 is 2,34%. Thus, for the period from January 2002 to December 2020, the expected duration of the current regime 1 is 43 months. In regime 2, the estimated duration is 4 months. The unconditional probability in periods of growth is 93.86% and 6.14% in periods of retraction.

Table 4. Estimation of the MS(2)-DR model.

Regime 1 (growth)			Regime 2 (recession)		
Parameter	Coefficient		Parameter	Coefficient	
$\mu(s_1)$	0,002211	(0,00091)**	$\mu(s_2)$	- 0,013859	(0,00791)*
σ^2	0,012881	(0,00070)***	σ^2	0,104184	(0,01991)***
ρ_{11}	0,9766	(0,01188)***	ρ_{12}	0,6821	(0,12870)***

Descriptive statistics	
Log-likelihood	611.259213
Linearity test $(\chi^2)(4)$	280.88 (0,0000)[1]
Normality test (χ^2)	4,7368 (0,2936)[1]
ARCH test (1-1)	5,1704 (0,4239)[1]
Pormanteau test - $\chi^2(36\,lags)$	35,7390 (0,4809)[1]

Transition probability matrix	Average duration period of regimes
Regime 1 Regime 2	Unconditional probability Duration period

Regime 1	0,9766 0,0234	Regime(1)	0,9386	43
Regime 2	0,3179 0,6821	Regime(2)	0,0614	4

Notes: ***, **, * denote statistical significance at the 1%, 5%, 10%, respectively.

Standard errors are in parentheses. $\left(^{1}\right)$ p value .

Source: Prepared by the author based on the research.

Figure 4 shows the behavior of the series of returns, smoothed and predicted probabilities for the regimes of states 1 and 2 of Brazilian industrial production. The upper panel presents the series of industrial production returns, and the middle and lower panels trace the smoothed probabilities for the market in regime 1 (growth) and regime 2 (recession or retraction), respectively.

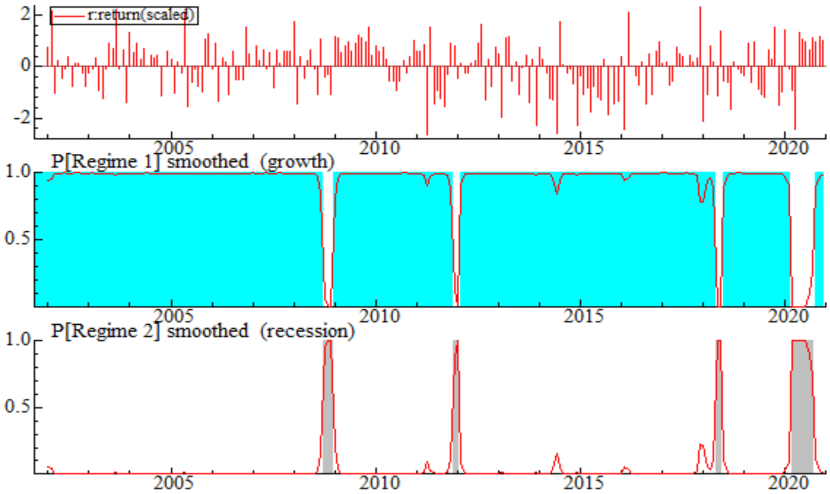


Figure 4. Smoothed probabilities of regimes 1 and 2 obtained in the MS(2)-DR model for industrial production returns in the period from January 2002 to December 2020.

From the estimated probabilities, the specific dates of the growth (1) and recession or retraction (2) regimes are obtained, shown in Table 5. Industrial production remained under the growth regime for five periods, totaling 214 months. In the recession or contraction regime (highlights the crises of 2008 and 2020), industrial production remained for about 10 months, being 3 months in the crisis of 2008 (period from October to December) and 7 months in the crisis of 2020 (period of March to September).

Table 5 - Specific dates of the regimes: MS(2)-DR model

Regime 1 (growth)			Regime 2 (recession)		
Period	Months	Probability	Period	Months	Probability
2002(1) - 2008(9)	81	0,994	2008(10) - 2008(12)	3	0,982
2009(1) - 2011(11)	35	0,984	2011(12) - 2012(1)	2	0,936
2012(2) - 2018(4)	75	0,983	2018(5) - 2018(6)	2	0,965
2018(7) - 2020(2)	20	0,986	2020(3) - 2020(9)	7	0,949
2020(10) - 2020(12)	3	0,951			

Source: Prepared by the author based on the research.

In the first period of crisis, starting in September 2008, there was a significant drop in the Bovespa index, caused by the subprime crisis triggered by the bankruptcy of one of the North American investment banks, Lehman Brothers, triggering a crisis in the international standard exchanges. After the bank's bankruptcy, the shares began to price an economic crisis, with a strong outflow of foreign investors from Brazil. The 2008 crisis was reflected in a strong international and

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domestic retraction, and a drop in commodity prices, with implications for the exchange rate that drastically depreciated, as well as a drop in industrial production in Brazil, especially in the last quarter of 2008, registering in October (-1,4%), November (-7,2%) and December (-12,4%) as a consequence in the comparison of the previous month. The sectorial performance of industrial productivity in 2008 registered seven sectors with significant decreases in productivity: Petroleum refining, Nuclear Fuels and Alcohol (-10,0%), Basic Metallurgy (- 5,4%), Machinery and Equipment (- 4,4%), Metal Products (-3,8%), Chemical Products (-3,0%), Extractive Industries (-1,8%) and Food and Beverages (-0,9%) (IEDI, 2009).

In the second period of crisis, which started in January 2020, industrial production had a negative impact due to the covid-19 pandemic, which has been generating strong turbulence in world markets and isolation policies to contain the pandemic progress, reflecting in the economy the effects of the closing of various economic activities (commerce, industry, aviation and tourism) .The industrial sector in the period from October 2019 to October 2020 had a loss of 5.6%. The drop in 2020 has been driven mainly by the lower production of motor vehicles, trailers and bodies (-34.4%), clothing and accessories (-29.1%), metallurgy (-11.2%), and machinery and equipment (-9.4%). Survey carried out by the National Confederation of Industry (CNI) in the period from 1 to 14 April 2020 for 1740 companies, 76% reported that they reduced or paralyzed production, 59% of entrepreneurs are struggling to meet current payments and 55% reported that access to working capital became more difficult. Among the measures taken in relation to the workforce, 15% of the companies dismissed.

IV. CONCLUSION

The objective of the present study is to analyze the evolution of industrial production returns in Brazil between January 2002 and December 2020, using the Markov switching dynamic regression (MS-DR) model. In the adjusted model, the mean and variance are modified according to the regime (state). In regime 1, the estimated monthly average return is 0,22% with a variance of 0,013. Regime 2 identifies a negative average monthly return of -1,38% with a variance of 0,104.

The Industrial production remained under the growth regime for five periods, totaling 214 months. In the recession or contraction regime (highlights the crises of 2008 and 2020), industrial production remained for about 10 months, being 3 months in the crisis of 2008 (period from October to December) and 7 months in the crisis of 2020 (period of March to September). Thus, for the period from January 2002 to December 2020, the expected duration of the current regime 1 is 43 months. In regime 2, the estimated duration is 4 months. The unconditional probability in periods of growth is 93.86% and 6.14% in periods of retraction.

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