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THE EFFECTS OF MACROECONOMIC VARIABLES ON BANK DEFAULT: A CASE STUDY IN BRAZIL

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ABSTRACT

With the end of the recession from 2014 to 2016, Brazil began a gradual recovery process, with a positive impact on some economic variables — among them, credit financing. Despite this, a robust recovery was not seen in 2019, and 2020 was marked by the arrival of the Covid-19 pandemic, which raises questions about the stability of the financial system and the control of defaults. Considering this, the present study explores how macroeconomic variables affected the default of a financial institution's credit portfolio between January 2014 and April 2019. To perform this analysis, we built a Vector Error Correction (VEC) model that captured the long-term relationships between the default of different credit products and the selected macroeconomic variables. The results indicate that the macroeconomic variables do in fact impact default, however, this behavior is not homogeneous. In general, different credit products respond in different ways to each of the macroeconomic entities: while part of our findings is in line with others in the literature, we also found surprising results for some of the studied relationships.

Contribution/Originality: This study contributes to the existing literature by demonstrating, through a case study in Brazil, the unique effects of the macroeconomic environment on the default of different and specific credit products, while most of the recent research focuses on aggregated data or default indexes.

1. INTRODUCTION

After the economic recession that hit Brazil between 2014 and 2016 (CODACE - Economic Cycles Dating Committee, 2017) the first signs of a gradual recovery were confirmed in 2017, when — after a real 8.6% drop during the crisis — there was a 1.3% growth in Gross Domestic Product (GDP) (IBGE - Brazilian Institute of Geography and Statistics, 2019). This recovery continued throughout 2018 and 2019, with positive impacts on different Brazilian macroeconomic variables in a period of historically low inflation and interest rates. However, this gradual improvement was interrupted by the Covid-19 crisis, which still sows uncertainty about the future of the Brazilian and global economy (BACEN - Central Bank of Brazil, 2020b).

Among the variables that were affected by this uncertainty are credit financing and default — both for individuals and companies. With regards to individuals, the increase in consumer confidence at the beginning of the economic recovery in Brazil resulted in annual credit growth rates of 8.4% in December 2018 — the highest level since December 2015, when this rate was 7.2% — maintaining the pace of growth until the end of 2019 (BACEN -

Central Bank of Brazil, 2020b). The types of credit that grew the most were consumer-oriented (credit card), vehicle financing and non-payroll loans. However, the (BACEN - Central Bank of Brazil, 2020b) estimates that, given the recent Covid-19 crisis, this growth will suffer severe reductions in the coming semesters, with an increase in debt restructuring operations to fit the payment capacity of households.

As for corporate credit, until 2019 there was a real growth in credit from free resources — which have been growing since mid-2017 —, with greater demand of credit for medium and large companies (BACEN - Central Bank of Brazil, 2020b; SERASA, 2019). However, as in the case of personal credit, the uncertainty brought about by the Covid-19 pandemic is difficult to measure, and should slow down the recent evolution of the credit portfolio, as well as the quality of its assets throughout 2020.

While there was an expansion of credit in recent periods, there was also a control of risk factors. According to the Banking Economics Report (BACEN - Central Bank of Brazil, 2020a) at the end of 2019 the general default rate of Brazilian's National Financial System, referring to operations overdue for more than 90 days, had been 2.9%. In this context, the report highlights that in December of that year, firms' defaults reached a historic low (since the beginning of the series, in March 2011), of 2.1%. For families, there was a 0.3 p.p. increase in relation to 2018, which brought the default rate to 3.5%.

Recent data shows that there seemed to be some stability in the national credit system, with an improvement in consumer confidence and a drop in default rates. Despite this, a robust recovery of the Brazilian economy was not seen in 2019 — with a 1.1% growth in GDP —, which raises questions regarding the evolution of the macroeconomic scenario and, also, of the financial system — especially at the current moment, in which expectations, as a result of the Covid-19 pandemic, are of an increase in defaults.

In face of so many uncertainties regarding economic recovery — which is necessary so that credit risks are kept under control — this work investigates how the behavior of national macroeconomic variables affects the default levels of a financial institution's portfolio containing different credit products. It is already known that a country's credit risk can be influenced by its economic conditions — however, there is no consensus on which macroeconomic factors are most relevant for determining default risks (Guo & Bruneau, 2014). The general goal of our study, then, is to confirm whether defaults behave as a function of a set of selected macroeconomic variables, and what is the direction of these effects.

Understanding this issue is important, since the resumption of growth must take place in a controlled manner, while maintaining — or improving — stability levels. The knowledge of how macroeconomic variables influence default behavior enriches the discussion and analysis of the economic scenario, at a time when expectations regarding the future are uncertain. To achieve the proposed goal, a Vector Autoregressive/Vector Error Correction (VAR/VEC) multivariate time series model was estimated, in which the set of endogenous variables is formed by the default of different credit products, and the exogenous variables are formed by a set of macroeconomic series.

The study is structured as follows: section 2 provides a brief literature review regarding credit and defaults; section 3 presents the methodology and data we used, the econometric tests performed, and the definition of the model; finally, section 4 consists of the results of the study, which is concluded with our final considerations in section 5.

2. CREDIT, DEFAULT AND MACROECONOMIC VARIABLES

The credit market is of fundamental importance for economic development, since it allows for the creation and anticipation of purchasing power, as well as investment possibilities, both for companies and individuals. Credit is seen by Schumpeter (1911) after all, as a lever for economic growth. Following this approach, Stiglitz and Weiss (1981) also argue that access to credit is one of the accelerators of a country's economic development. Without obtaining resources, companies reduce their production, revenue and investment capacity, as well as their process of creating new jobs.

However, one cannot think about credit market operations without concerns about the risks involved in such operations. Even with the adoption of several risk assessment models, the real result of a credit operation is only known when it is settled, that is, at the end of the stipulated period. The uncertainty regarding the results of these operations is what creates credit-risk. Thus, credit risk is the possibility that the operation will not end according to the agreed terms (Securato, 2013). The main risk of a credit transaction is, therefore, default. Following the most common definition, including the one from the IMF - International Monetary Fund (2006) default happens when interest and principal payments are delayed by 90 days or more.

Since the subprime crisis in 2008, there has been a growing interest in the determinants and effects of default, as it is argued in recent literature that the volume of default is a good proxy for measuring the financial stability of an economy (Guo & Bruneau, 2014; Podpiera & Weill, 2008; Tabak, Craveiro, & Cajueiro, 2010). For example, business cycles are one of the main factors determining variations in a portfolio's default. The cycle can directly impact default due to the effect of a macroeconomic deterioration in customers' risk (Yanaka, 2014).

Furthering this analysis, Bonfim (2009) argues about the importance of understanding whether credit risk is driven mainly by the particular characteristics of a country's companies or by the systemic factors of an economy. The author uses data from more than 30 thousand firms, and shows that specific characteristics of companies — such as past default, financial structure, profitability, liquidity, investment policy and sales performance — have an influence on the probabilities of default, however, when macroeconomic variables are also taken into account the results improve substantially. In her work, GDP growth showed a strong negative impact on companies' defaults. The study also presents indications that, in periods of economic growth, economic agents tend to take excessive risks.

Indeed, there are robust results in the literature about the impacts of macroeconomic conditions on default risks, although there is no general consensus on which specific macroeconomic factor is more relevant (Guo & Bruneau, 2014). The study conducted by Jakubik (2007) based on aggregate data of the Czech economy, finds strong relationship between the quality of bank portfolios and the macroeconomic environment. The author's results show that higher GDP growth rates lead to lower default levels, and that higher interest rates imply greater default, which is in line with economic intuition. In addition, the inclusion of inflation in the model (resulting in a negative coefficient, that is, in lower default) also shows that default depends on the real interest rate, not the nominal one.

Following a similar idea, but for the Swedish economy, Sommar and Shahnazarian (2008) estimate the relationship between the Expected Default Frequency (EDF) of Swedish firms and the variables of inflation, industrial production and short-term interest rate. Using a VEC model for data between 1997 and 2006, their results showed that increases in industrial production implied in lower probabilities of default. For inflation, their findings are opposite to those of Jakubik (2007): the variable's coefficient proved to be positive, leading to evidence that rising inflation resulted in higher probability of default. The short-term interest rate was the variable with the greatest impact among the three and was positively related to the probability of default.

Other studies show the relevance of interest rates on defaults, as can be expected considering economic intuition. Laurin and Martynenko (2009) also for the Swedish economy, found a positive relationship between interest rates and the default probability of the corporate sector, in line with the work of Sommar and Shahnazarian (2008). In addition, industrial production and the exchange rate when lagged by one year had a major negative impact on the probability of default. According to the authors' model, these variables explain 75% of the changes in the probability of default for large firms and 68% for small and medium-sized firms.

Therefore, considering the results found by other studies in the international literature, and the apparent disparity among some of these findings, we explore the relationship between macroeconomic variables and default in Brazil, hopping to contribute to the international discussion. The following chapter describes the methodology we used to do so.

3. METHODOLOGY

To conduct our analysis, we built a VAR/VEC multivariate time series model, since the default behavior of a credit portfolio was analyzed as a function of the selected macroeconomic variables considering their respective trajectories over time. VAR are multivariate models that allow for the expression of complete economic models and the estimation of its parameters (Bueno, 2011). In addition, a central feature of VAR models is that they examine linear relationships between each variable and their lagged values, in addition to that of other variables, becoming models that include endogenous and exogenous variables.

As for VEC models, these are, in short, VAR models in which an error correction term is present, and a cointegration between the variables exist. Therefore, they are more complete VAR models that identify common dynamics for non-stationary series, both for short and long terms (Bueno, 2011). The choice of VEC on this work is justified by its power to capture common trends between the series, and because it also provides a feedback effect between default and its explanatory variables (Sommar & Shahnazarian, 2008). Since our goal is to find a long-term relationship between default and macroeconomic variables, we expect that there will be cointegration between the two series. In this case, then, the VEC model can be considered. For the estimation, we used the software *EViews®*.

3.1. Data

Our database is formed by two sets of data: the default of the selected credit products, used to build the endogenous variables, and the selected macroeconomic series, used to build the exogenous variables. The data used in the construction of default was obtained internally in a Brazilian financial institution and refers to both individuals and firms. We used the balances of the six most relevant credit products offered by the financial institution, from January 2014 to April 2019, as below:

- Total_Balance: represents the sum of the accounting balance of each product in each month.
- NPL_Balance: represents the sum of the non-performing loans (more than 90 days overdue) of each product in each month.

The endogenous variables were formed by the monthly division of defaulted balances (over 90 days) by their total balance for 6 different credit products. Table 1 presents the selected products and the variable name we used for each one.

Table-1. Selected products description.

Variable	Product description
Product_1	Loan renegotiations for firms
Product_2	Loan renegotiations for households
Product_3	Payroll-deduction loans (offered by third parties)
Product_4	Payroll-deduction loans (offered by the financial institution)
Product_5	Working capital
Product_6	Overdrafts

Figure 1 shows the behavior of default for the six selected products throughout the period.

As for the macroeconomic variables, these were obtained from the Central Bank of Brazil (BACEN - Central Bank of Brazil, 2019) and the *Instituto de Pesquisa Econômica Aplicada* (IPEA - Institute of Applied Economic Research, 2019):

- IBC_BR: represents the Economic Activity Index — which can be used as a proxy for GDP — with the year 2002 as the base date (100). We use IBC instead of GDP since the former is available in monthly data, while the latter is not.
- SELIC: represents the interest rate, and is formed by the monthly accumulated variation of Brazilian's basic interest rate (SELIC).

- IPCA: represents inflation, and is formed by the monthly percentage of the national Consumer Price Index.
- INCC: this variable is formed by the monthly percentage of the National Construction Costs Index, in Brazil.
- Unemployment: unemployment rate for Brazil as a percentage of the workforce.
- Commitment: commitment of households' income, as percentages.

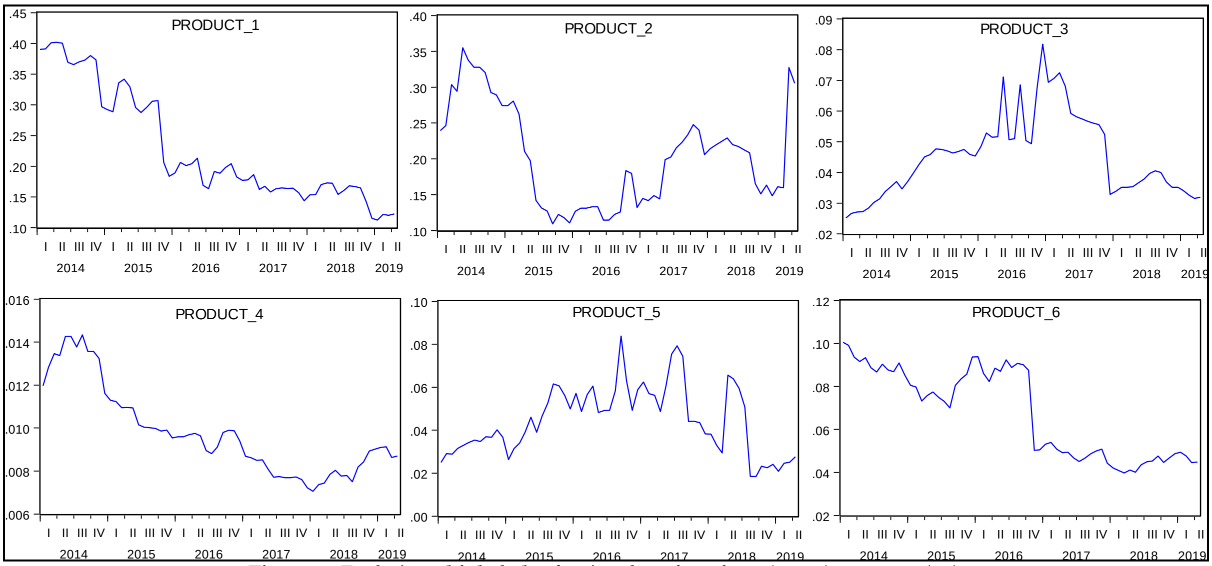

Figure-1. Evolution of default for the six selected products (2014/01 to 2019/04).

In Figure 2 we can see a set of graphs that show us the behavior of each of these macroeconomic variables.

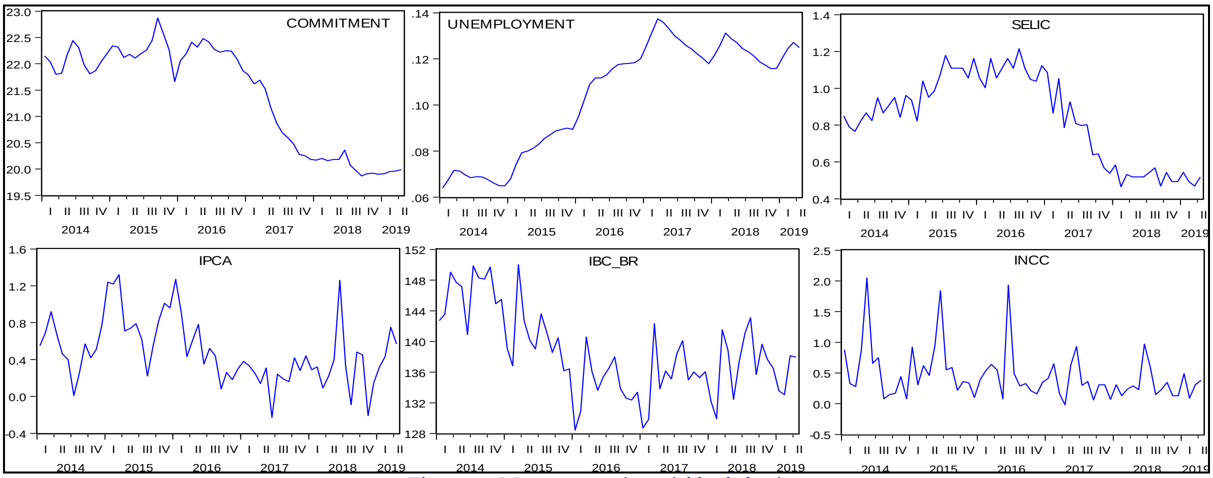

Figure-2. Macroeconomic variables behavior.

Particularly noteworthy, are the variables Commitment, Unemployment and SELIC. The first shows a sharp drop in households' income commitment from the beginning of 2016, then it starts to grow minimally in the beginning of 2018, only to suffer another fall afterwards. The Unemployment variable, in turn, has grown strongly since 2015, as a result of the constant recession that has hit the country since the second quarter of 2014. The third — SELIC — clearly shows us the reductions in the basic national interest rate after 2016, with a stronger reduction in the second half of 2017. It should also be highlighted that the INCC variable has three peaks in the level of construction costs. This variable will later be evaluated for the existence of outliers.

3.2. Econometric Tests and Model Definition

Before defining the model, it was necessary to analyze and treat the data, in order to determine if the regressions should be performed using a VAR or VEC model. Figure 3 presents a flowchart with the steps taken in this definition.

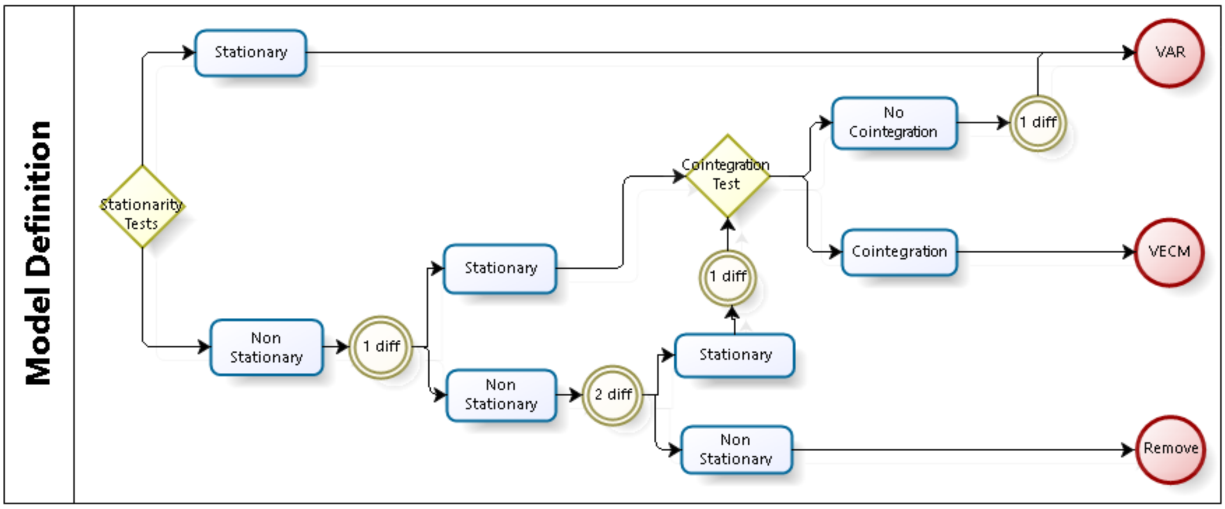

Figure-3. Necessary steps for the model definition: VAR or VEC.

We can see that the first step consists on testing the stationarity of all variables. For that, we used the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests, testing their hypotheses with intercept, with trend and intercept, and without any of these (only the explanatory variables). The results for the first tests (level variables) are shown in Table 2.

Based on the tests performed, we can see that all endogenous variables fail to reject the null hypothesis of non-stationarity. As for the exogenous variables, the tests indicate that INCC and IPCA are stationary with an order of integration I(0). The other exogenous variables are non-stationary in level.

As the endogenous variables are non-stationary, the option of running a VAR model directly with the variables at level is discarded. Considering this, we checked whether the endogenous variables would be stationary in their first difference. The results are shown in Table 3 and, based on both tests (ADF and PP), we can infer that all variables are integrated in their first order that is, they become stationary after the first difference.

As now the endogenous variables are all of the same order of integration, it is possible that there is cointegration in the estimated series (Bueno, 2011) which was tested followingly Table 4. It is important to note that we first ran a test only with the endogenous variables, solely to test whether there would be cointegration between them, and whether we could consider the use of a VEC model.

Table 4 shows the results for the Johansen cointegration test summarized for the five existing specifications. The results confirm that there is at least one cointegration and, therefore, a VEC model approach is possible. It is important to stress that at the end of the modelling process, the final cointegration test will be presented again with the exogenous variables included.

3.3. Additional Treatment and Tests

Before starting the modeling of the VEC model, we checked the possible existence of outliers in all variables. The boxplot graphs on Figure 4 show that the Product_3 variable has an outlier and the INCC variable has 3 outliers. In addition to these outliers, Product_3 also has two other points that appear to behave differently from the rest of the series. Therefore, we treated them using dummy variables.

Table-2. Stationarity tests (in level variables).

Variable	Test	t-statistic			
		Intercept	Trend and intercept	None	I
Endogenous Variables					
Product_1	ADF	-1.425285	-2.269412	-3,120442***	
	PP	-1.686799	-2.189483	-5,498409***	
Product_2	ADF	-1.480235	-1.204238	-0.216779	
	PP	-1.632402	-1.291076	-0.229777	
Product_3	ADF	-1.641201	-1.069681	-0.170231	
	PP	-2.064067	-1.80113	-0.308128	
Product_4	ADF	-1.067865	-1.09035	-1.196938	
	PP	-1.168082	-1.518087	-1.06991	
Product_5	ADF	-2,683606*	-2.636024	-0.817827	
	PP	-2,700414*	-2.472379	-0.473385	
Product_6	ADF	-1.409601	-2.169613	-1,581178*	
	PP	-1.413109	-2.262747	-1,616659*	
Exogenous Variables					
Commitment	ADF	-0.21453	-1.74231	-1.476976	
	PP	-0.331668	-1.771829	-1.377937	
Unemployment	ADF	-2,910779**	-1.672244	-0.113197	
	PP	-1.45565	-1.061204	1.461087	
Ibc Br	ADF	-3,745412***	-4,631857***	-0.848055	
	PP	-3,480289**	-4,596482***	-0.53445	
Incc	ADF	-6,559357***	-7,015965***	-2,528315**	I(0)
	PP	-6,562155***	-6,964901***	-3,716333***	I(0)
Ipca	ADF	-3,930456***	-4,341574***	-2,127767**	I(0)
	PP	-3,895948***	-4,300169***	-2,127767**	I(0)
Selic	ADF	-0.308697	-2.053906	-0.719339	
	PP	-0.84045	-1.978441	-0.802582	

Note: *, **, *** indicates rejection of the null hypothesis at 10%, 5% and 1% respectively.

Table-3. Stationarity tests (endogenous variables in first difference).

Variable	Test	t-statistic			
		Intercept	Trend and intercept	None	I
ΔPRODUCT_1	ADF	-7,161761***	-7,288386***	-6,841463***	I(1)
	PP	-8,960674***	-12,47419***	-6,877734***	I(1)
ΔPRODUCT_2	ADF	-8,061592***	-8,155521***	-8,120830***	I(1)
	PP	-8,061706***	-8,151922***	-8,118255***	I(1)
ΔPRODUCT_3	ADF	-9,092882***	-9,614371□**	-9,166151***	I(1)
	PP	-9,766272***	-9,601960***	-9,854706***	I(1)
ΔPRODUCT_4	ADF	-6,816539***	-6,879568***	-6,710745***	I(1)
	PP	-6,820062***	-6,863412***	-6,731646***	I(1)
ΔPRODUCT_5	ADF	-7,579116***	-5,550477***	-7,642000***	I(1)
	PP	-8,823014**□	-9,750728***	-8,935724***	I(1)
ΔPRODUCT_6	ADF	-7,541959***	-7,495529***	-7,439492***	I(1)
	PP	-7,535389***	-7,487014***	-7,431293***	I(1)

Note: *, **, *** indicates rejection of the null hypothesis at 10%, 5% and 1% respectively.

Table-4. Johansen cointegration test (endogenous variables).

Data Trend	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	1	1	1	1	1
Max-Eig	1	0	0	0	0

Note: Selected (0.05 level*) Number of Cointegrating Relations by Model.
*Critical values based on MacKinnon, Haug, and Michelis (1999).

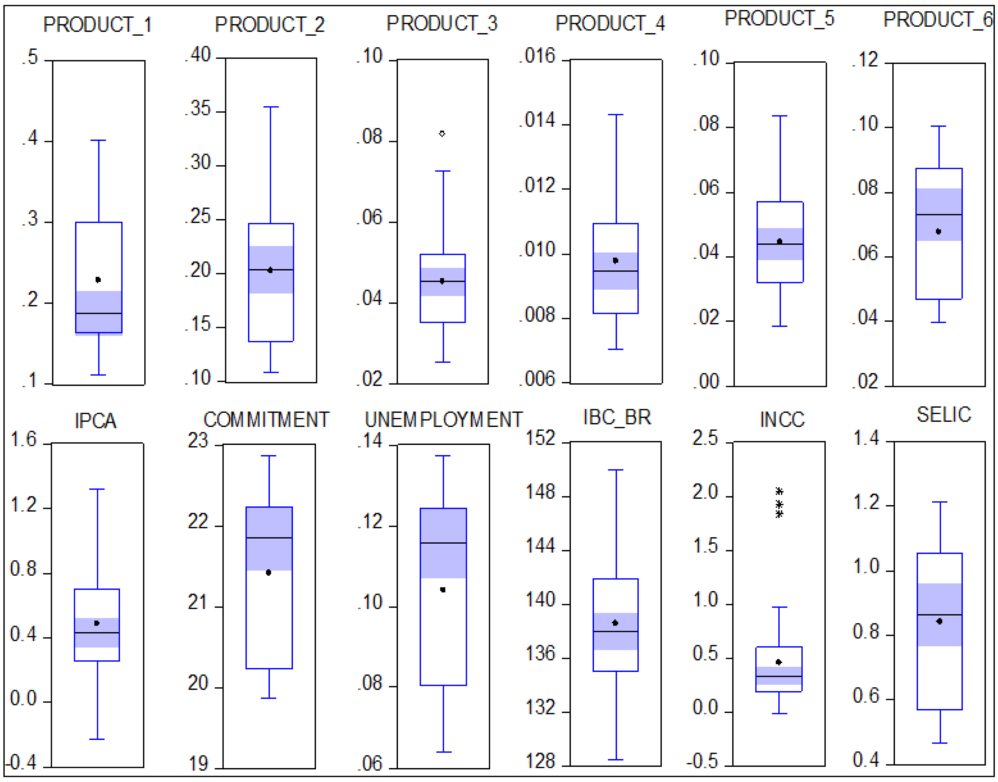

Figure-4. Boxplot graphs.

The dummy variables we tested were: *dummy_incc_outliers* (receiving 1 for the periods 201405, 201506 and 201606, and 0 for the remaining) and *dummy_prod3_outliers* (receiving 1 for the periods 201605, 201608 and 201612, and 0 for the others). Besides these, considering the behavior of the variables at their level Figure 2, we decided to create other dummy variables so that more conditions could be verified, which were:

- PRODUCT_5: removal of 3 high-peaked intervals. Creation of the variable *dummy_prod5* (1 for the periods of 2016_07 to 2016_11, 2017_04 to 2017_09 and 2018_03 to 2018_08, and 0 for the remaining).
- PRODUCT_6: a test removing the high periods between 2015_08 and 2016_11, which seems to interrupt a downward trend on the variable, and another test assuming a possible structural break, since the variable appears to maintain a certain level from the beginning of the series until 2016_10, and then has a sudden drop in 2016_11, following this new level until the end. Creation of the variables *dummy_prod6_1* (1 for the periods between 2015_08 and 2016_11, and 0 for the remaining); and creation of the variable *dummy_prod6_2* (1 from the beginning of the series until 2016_10 included, and 0 to the rest).
- PRODUCT_2: this variable showed a very volatile behavior and, therefore, trend break dummies (for when the series presents very strong upward trends) were tested. Creation of the variable *dummy_prod2* (1 for the periods between 2014_01 to 2014_05, 2016_12 to 2017_10 and 2019_02 to 2019_03, and 0 for the rest).
- IBC_BR: this variable seems to have a structural break. Therefore, we created a dummy to separate the periods (1 for the period between 2014_01 to 2015_08, and 0 for the rest of the series).

The next step in the process consisted on the identification of the ideal level of lags to be considered for endogenous variables. For this, we used the Order Selection Criteria, through Likelihood Ratio (LR) and Final Prediction Error (FPE) tests, as well as with Akaike (AIC), Schwarz (SC) and Hannan-Quinn (HQ) information criteria. The result for a test of up to 6 lags can be seen in Table 5. According to the information criteria, only 1 lag should be adopted, that is, the endogenous variables were analyzed until their first lag, as confirmed by the largest number of tests (FPE, SC and HQ).

Table-5. Order selection criteria.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1011.517	NA	3.52E-23	-34.67298	-34.45984	-34.58996
1	1295.489	499.4004	6.86E-27*	-43.22377	-41.73172*	-42.64259*
2	1320.222	38.37807	1.05E-26	-42.83524	-40.06430	-41.75590
3	1349.165	38.92300	1.49E-26	-42.59188	-38.54205	-41.01439
4	1380.620	35.79379	2.15E-26	-42.43516	-37.10643	-40.35952
5	1421.322	37.89559	2.68E-26	-42.59732	-35.98970	-40.02352
6	1505.276	60.79371*	9.9E-27	-44.25088*	-36.36436	-41.17892

Next, we conducted Pearson's Correlation and Granger Causality tests, in order to determine the inclusion and ordering[1] of the endogenous and exogenous variables in the model. The results of these analysis can be found in the Appendices Table A1 for endogenous variables and Table A2 for exogenous variables). With respect to endogenous variables, it was defined that the first variable in the ordering would be PRODUCT_3 (which causes 3 other variables), the second would be PRODUCT_5 (which is caused by PRODUCT_3 and still causes 2 other variables) and the third would be PRODUCT_4 (which is caused by PRODUCT_5). Continuing, we ran a regression using a preliminary VEC model, containing only endogenous variables, in order to evaluate the model without the presence of macroeconomic variables. The preliminary results showed several non-significant parameters and a very low R^2 for most products. Thus, we hoped that with the inclusion of the exogenous and dummy variables the model would present more adjusted and robust results.

Regarding the exogenous variables, we evaluated which ones "Granger-caused" the endogenous variables and, after that, we analyzed the correlation between them. Only the exogenous variables that "Granger-caused" the dependent variable, with a significance level until 10% and which had correlations above 0.4, were maintained for the next round of tests. From the results, we decided to test the following exogenous variables (with their respective lags) in the models:

- Commitment: in level and with the *lags* 1, 2, 3, 7, 10, 11 e 12.
- Unemployment: in level and with the *lags* 1, 2, 7, 8, 9, 10, 11 e 12.
- IBC_BR: in level and with the *lags* 1, 2, 3 e 11.
- INCC: *lag* 2.
- IPCA: in level and with the *lags* 4, 5, 7, 8, 9, 11 e 12.
- SELIC: in level and with the *lags* 1, 2, 3, 4, 5, 9, 10 e 11.

From these variables, we simulated different models in order to seek the best possible adjustment considering statistical significance, economic sense, and R^2 Table A3 in the Appendices summarizes the R^2 of the main tested models). The model is specified by the Equation 1 below:

$$\Delta x_t = \delta_0 + \Gamma_1 \Delta x_{t-1} + \varphi_1 z_t + \varphi_2 z_{t-p} + \omega d + \alpha\beta x + \varepsilon_t \quad (1)$$

Where x_t represents the endogenous and dependent variables (Product_3, Product_5, Product_4, Product_6, Product_1 e Product_2), while x_{t-1} is their first lags. The term z_t represents the exogenous variables, z_{t-p} the exogenous variables in their "p" lags and ωd contemplates the set of dummy variables created. The coefficients that

[1] As stated by Bueno (2011) VAR models do not allow for the identification of all parameters of its structural form, unless some additional restrictions are imposed and the model is conducted in its reduced form, for later recovery of the structural parameters. For this, the Cholesky decomposition process forces the imposition of restrictions, stipulating that certain matrix coefficients are equal to zero. In this case, since the decomposition occurs in a triangular form, zero is imposed on the coefficients located in the upper diagonal portion of the matrix. It is for this reason that the ordering of variables in the matrix model is important: it defines the shape of the constraints, so that different orderings generate different constraints.

form the α matrix describe the adjustment speed of the endogenous variables, and the cointegration vector β describes the long-term relationships. Finally, ε_t represents the error term.

4. RESULTS

Based on the criteria described in section 3, we found that the best VEC model would be number 23. Considering that the table with the regression results is quite extensive, we decided to include it in Appendix A4. First, as we analyzed the default from six different credit products, we found that the impacts of the macroeconomic variables were mostly different for each type of product – which is not unexpected, since as argued by Sommar and Shahnazarian (2008) the possible effects of macroeconomics variables on default may be ambiguous and difficult to know a priori, and thus, this is essentially an empirical issue.

Regarding the interest rate (SELIC variable), following economic intuition and the revised literature, we expected that this variable would have positive effects on default. This was, in fact, the result we found for products 1 and 2 (firms and families' renegotiations, respectively) and 5 (working capital), that is, an increase in the interest rate implies in higher default for these products, possibly because they are transactions involving floating rates and, therefore, increases in the market's interest rates tend to increase debts. This way, we can see that this important macroeconomic variable has real impacts on defaults of both families and companies. Positive relationships between interest rates and defaults are also found by Jakubik (2007); Sommar and Shahnazarian (2008) and Laurin and Martynenko (2009).

However, for products 3 and 4 (payroll-deduction loans) and 6 (overdraft), the results indicate a negative impact of the interest rate on these products, which goes against the overall expected results. In the case of payroll-deduction loans specifically, we did not expect clear effects from the basic interest rate (SELIC), since the negotiated rate when these products are contracted is fixed, and so, they do not suffer the effects of changes in interest rates over time. As for overdraft, the negative relationship between its default and the interest rate is difficult to explain, but one hypothesis is that, since in Brazil the overdraft rates are extremely high, it is possible that increases in the interest rate create incentives for consumers to prioritize the payment of this this high-cost debt as soon as possible, reducing default.

As for the commitment of households' income and unemployment, considering the nature of what is measured by these variables, we expected relevant and direct results only on the default of products contracted by families. Generally speaking, we expected a positive effect on default, however, the results we found were not clear, with a great number of alternating effects, between positive and negative, depending on the lags of the exogenous variables and the analyzed products. Thus, a more in-depth analysis based on the study carried out for these variables was not possible.

Moving on, for the economic activity index (IBC_BR variable), the expected result was of a negative effect on defaults, since normally an improvement in economic activity implies in greater capacity of families and companies to honor with their commitments. Indeed, the results of our model showed that economic activity has a negative effect on the default of firms' and families' renegotiations (products 1 and 2), payroll-deduction loans (products 3 and 4) and working capital (product 5). Considering that the IBC index is used as a parameter for assessing economic growth, and that it exerts a great influence on GDP estimates, it makes sense that an improvement in activity and growth would have negative impacts on default. These results are in line with those evidenced by Jakubik (2007) and Bonfim (2009) for GDP, and by Sommar and Shahnazarian (2008) and Laurin and Martynenko (2009) for industrial production.

On the other hand, we found a positive effect of economic activity on the default of overdrafts (product 6). Although this was not the result we expected, it is possible that in a scenario of growing economic activity, there would be a tendency for families to increase their consumption and expenses, resulting in an increase in overdraft use, given the availability and ease of access to this credit product.

For inflation – represented by the IPCA variable – similarly to Sommar and Shahnazarian (2008) we expected a twofold effect for firms: first, an increase in prices of production factors would tend to increase firms' costs, resulting in poorer credit quality and higher default; on the other hand, an increase in final products prices could lead to higher revenues for firms, improving credit quality and decreasing their defaults. Thus, the direction of this effect depends on the structure of the market in question (Sommar & Shahnazarian, 2008).

Observing the results for firms related products, we found that for renegotiations (product 1), the impact of inflation on default was negative, indicating that the effect of companies' revenues described above may have been stronger than an increase in production costs. For the working capital (product 5), however, we found positive effects on default, which possibly indicates that for the firms contracting this product, the factors of production effect dominated other inflation impacts, resulting in a drop in credit quality and increasing defaults - following some of the results found by Sommar and Shahnazarian (2008).

Regarding the products contracted by families, economic intuition tells us that an increase in inflation should result in higher default, since there would be a decrease in households' disposable income. However, this result was only found for the payroll-deduction loan represented by product 4. For the remaining of households related products, inflation had a negative or ambiguous impact on defaults. Apparently, then, the impacts of inflation on household defaults are not clear and should be further investigated by future studies. Despite this, negative effects of inflation on default have already been found in the literature. Jakubik (2007) argues that the combined result between nominal interest rates and the negative effect of inflation indicates that default depends on the real, and not nominal, interest rate.

We can see, then, that macroeconomic variables did have effects on the default of our selected products. Although some of the results were ambiguous, our model passed all the robustness tests and proved to be well adjusted, what guarantees the reliability of our results. First, we conducted the Jarque-Bera test with Cholesky orthogonalization, which confirmed the normality of the estimated residuals. Then, we performed the Breusch-Godfrey test - also known as Lagrange Multiplier (LM) test - confirming that the residuals do not present serial autocorrelation. In addition, it is essential that the variance of the residuals is constant, which was confirmed by the White test. Finally, analyzing the model's unit-root graph we can affirm that the model is stable. The results for these procedures can be found in Appendix A5.

As for the final cointegration of the series, to assess this issue we ran a new Johansen test, and the results are shown in Table 6. We can see that there are 6 cointegration vectors in the final model, confirming the existence of a long-term relationship between macroeconomic variables and the default of the selected products. The trace test and the max test were also performed individually, considering the third specification of the deterministic function, confirming the existence of the 6 cointegration vectors. These results are available in Appendix A6.

Table-6. Johansen cointegration test (final model).

Data Trend:	None	None	Linear	Linear	Quadratic
Test Type	No Intercept	Intercept	Intercept	Intercept	Intercept
	No Trend	No Trend	No Trend	Trend	Trend
Trace	5	5	6	5	6
Max-Eig	5	5	6	5	6

Note: Selected (0.05 level*) Number of Cointegrating Relations by Model.
*Critical values based on MacKinnon et al. (1999).

In addition, the normalized cointegration vector (which represents the long-term relationships between the model's variables) and the speed of adjustment parameter (alpha) were calculated. The tables with these results were included in Appendices A7 and A8, respectively. Finally, Appendix A9 contains the comparison between the actual results and the ones fitted by the model.

5. CONCLUSIONS

The year of 2020 started with a shock of uncertainty regarding the future of economies around the world. The crisis caused by the Covid-19 pandemic raised concerns about — among many essential socioeconomic topics — the global macroeconomic fundamentals, curbing expectations of economic growth. Considering this, we see the supply and use of credit as one of the main instruments to be used in the process of resuming growth, since it has the potential to anticipate investments and strengthen consumption. This scenario reinforces the importance of a stable financial system, with quality credit to be used by families and companies throughout the economic recovery.

In this sense, understanding the relationship between the macroeconomic environment and credit risk is important for financial institutions to keep their default levels under control. Thus, this work investigated how a group of macroeconomic variables affected the default of different credit products offered by a Brazilian bank. Our paper stands out from others found in the literature as it is a case study, while, in general, other works tend to use a default rate (such as the EDF) as the object of study. The benefits of our approach lie in the possibility of capturing the unique effects of the macroeconomic environment on the default of different and specific credit products, given that, as demonstrated by the results, they do not respond homogeneously to macroeconomic variables.

In summary, the clearest and closest results to the studied literature were found for the variables representing the basic interest rate (SELIC), economic activity (IBC_BR) and inflation (IPCA). In the case of the interest rate, we found positive effects on the default of working capital and the default of renegotiations from firms and households. Regarding economic activity, there is evidence that improvements on this index reduce default of the firms' and households' renegotiations, as well as payroll-deduction loans and working capital. Finally, for inflation, we found a negative effect on the default of firms' renegotiations, and a positive effect on the default of working capital and on one of the payroll-deducted loans. All these findings followed the expected results according to studies carried out in the literature.

At the same time, some unexpected results were found. The interest rate appears to have had a negative effect on payroll-deducted loans and overdrafts. Regarding the former, as discussed in the results section, it is possible that the relationship between these variables is not very clear, since these products are contracted upon a fixed interest rate. As for the overdraft result, we raised the hypothesis that this negative effect could be related to the extremely high interest rates charged for overdrafts in Brazil.

As for economic activity, the only surprising result was for the default of overdrafts, for which we identified a positive impact from the IBC_BR variable. In the results section, we discussed the possibility that an economy with constantly growing activity could result in greater debts and defaults by families, due to strong tendencies to consumption and the ease of access to overdraft — which is often most people's first option, as it is hired automatically and, not infrequently, without consumers being fully aware of it.

Thus, considering that the interest rate and the economic activity (variables for which we consider having found the most robust evidence in our work) had a negative effect on overdraft's default, we can see that this is a product that has a surprising behavior in response to the macroeconomic environment. In view of this evidence and, since this is an important credit product for the Brazilian economy — since it is popularly used and well disseminated among consumers —, we conclude that it deserves greater attention from financial institutions and also from future research, which can further test the hypotheses raised here.

We can see, then, that macroeconomic variables cause different effects on default, depending on the type of credit product that is being examined. This is an interesting finding, as it demonstrates that the default behavior for different products does not follow a unique pattern, and that this can be caused by different reasons which are intrinsic to each type of product, market structure or consumer. This, in turn, highlights the importance of case studies and their power to capture unique effects, which can sometimes be lost on more generalized studies.

Regarding the implications of this research's results, we believe that the confirmation — by future works, carried out with more financial institutions — of the evidence here presented, can assist financial institutions in the development and application of strategies for their credit products sales, risk control, and the anticipation of defaulting consumers' behavior. For the public sector, as already mentioned, it must pay attention to the maintenance of a healthy and stable macroeconomic environment, which enables responsible credit supply and consumption — elements that will be necessary for the coming economic recovery.

Finally, the main limitations of this study include the short period for which the data was obtained, and the fact that the analyzed portfolio is from a specific Brazilian bank, what imposes a natural limitation of case studies, which is the difficulty of generalizing results. Therefore, we encourage that future studies investigate the relationships here explored for other countries, also using a larger sample that covers at least one complete economic cycle. In addition, we suggest a more in-depth analysis of the effects of committed income and unemployment on defaults, given that our results were not conclusive for these variables. Lastly, the impacts of inflation on household defaults should also be further explored by future research.

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REFERENCES

BACEN - Central Bank of Brazil. (2019). SGS - time series management system. Retrieved from: https://www3.bcb.gov.br/sgspub/consultarvalores/telaCvsSelecionarSeries.paint. [Accessed March 30, 2020].

BACEN - Central Bank of Brazil. (2020a). Banking economics report. Retrieved from: https://www.bcb.gov.br/content/publicacoes/relatorioeconomiabancaria/reb_2019.pdf. [Accessed April 12, 2020].

BACEN - Central Bank of Brazil. (2020b). Financial stability report. Retrieved from: www.bcb.gov.br/content/publicacoes/ref/202004/RELESTAB202004-refPub.pdf. [Accessed April 21, 2020].

Bonfim, D. (2009). Credit risk drivers: Evaluating the contribution of firm level information and of macroeconomic dynamics. *Journal of Banking & Finance, 33*(2), 281–299.Available at: https://doi.org/10.1016/j.jbankfin.2008.08.006.

Bueno, R. D. L. D. S. (2011). *Time series econometrics* (2nd ed.). São Paulo: Cengage.

CODACE - Economic Cycles Dating Committee. (2017). Announcement of dating of Brazilian monthly cycles. Retrieved from: https://portalibre.fgv.br/estudos-e-pesquisas/codace/codace.htm. [Accessed April 8, 2020].

Guo, L., & Bruneau, C. (2014). Macroeconomic variables and default risk: An application of the FAVAR model. *Political Economy Review, 124*(5), 817-857.

IBGE - Brazilian Institute of Geography and Statistics. (2019). Produto interno bruto – PIB. Retrieved from: http://www.ibge.gov.br/. [Accessed March 30, 2020].

IMF - International Monetary Fund. (2006). Financial soundness indicators: Compilation guide 2006 - contents. Retrieved from: https://www.imf.org/external/pubs/ft/fsi/guide/2006/index.htm. [Accessed April 11, 2020].

IPEA - Institute of Applied Economic Research. (2019). Retrieved from: http://www.ipeadata.gov.br. [Accessed March 30, 2020].

Jakubik, P. (2007). Macroeconomic environment and credit risk. *Czech Journal of Economics and Finance, 57*(1-2), 60-78.

Laurin, M., & Martynenko, O. (2009). The influence of macroeconomic factors on the probability of default: A study of the relationship between default probabilities and macroeconomic variables (Thesis). Retrieved from: https://lup.lub.lu.se/luur/download?func=downloadFile&recordOId=1486524&fileOId=1647104. [Accessed April 18, 2020].

MacKinnon, J. G., Haug, A. A., & Michelis, L. (1999). Numerical distribution functions of likelihood ratio tests for cointegration. *Journal of Applied Econometrics, 14*(5), 563- 577.Available at: https://doi.org/10.1002/(sici)1099-1255(199909/10)14:5%3C563::aid-jae530%3E3.0.co;2-r.

Podpiera, J., & Weill, L. (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability, 4*(2), 135-148.Available at: https://doi.org/10.1016/j.jfs.2008.01.005.

Schumpeter, J. (1911). *The theory of economic development*. USA: Harvard University Press.

Securato, J. R. (2013). *Credit: Risk analysis and assessment* (2nd ed.). São Paulo: Saint Paul.

SERASA. (2019). Economic indicators. Retrieved from: https://www.serasaexperian.com.br/amplie-seus-conhecimentos/indicadores-economicos. [Accessed April 28, 2020].

Sommar, P. A., & Shahnazarian, H. (2008). Macroeconomic impact on expected default frequency. *SSRN Electronic Journal*.Available at: https://doi.org/10.2139/ssrn.1088626.

Stiglitz, J. E., & Weiss, A. (1981). Credit rationing in markets with imperfect information. *The American Economic Review, 71*(3), 393-410.

Tabak, B. M., Craveiro, G. L., & Cajueiro, D. O. (2010). Bank efficiency and default: Causality tests. Retrieved from: https://www.bcb.gov.br/pec/wps/port/TD220.pdf. [Accessed April 18, 2020].

Yanaka, G. M. (2014). Tests in risk management and banking regulation (Thesis). Retrieved from: https://bibliotecadigital.fgv.br/dspace/handle/10438/13133. [Accessed March 28, 2020].

APPENDICES

Appendix-A1. Granger Causality test (endogenous variables).

Null Hypothesis:	F-Statistic	Prob.	Sig.
Product_5 does not Granger Cause Product_3	4.44168	0.039259115	**
Product_5 does not Granger Cause Product_4	3.39113	0.070492224	*
Product_3 does not Granger Cause Product_5	6.96753	0.010561746	***
Product_3 does not Granger Cause Product_2	3.55489	0.064214489	*
Product_3 does not Granger Cause Product_4	7.38038	0.008603390	***

Note: *, **, *** indicates rejection at 10%, 5% and 1% respectively.

Appendix-A2. Granger Causality test and Correlations (exogenous variables).

Null Hypothesis:	F-Statistic	Prob.	Sig	Correl.	Select
Lags: 12					
Commitment does not Granger Cause Product_5	1.76243	0.10785	*	0.6564	
Commitment does not Granger Cause Product_6	4.44830	0.00062	***	0.5287	
Unemployment does not Granger Cause Product_6	2.18141	0.04516	**	-0.8845	
INCC does not Granger Cause Product_6	2.55014	0.02118	**	0.2529	x
INCC does not Granger Cause Product_1	2.05008	0.05931	**	0.2173	x
IPCA does not Granger Cause Product_2	2.20353	0.04314	**	-0.3784	x
Commitment does not Granger Cause Product_4	1.90708	0.07987	*	0.2352	x
Unemployment does not Granger Cause Product_4	3.67742	0.0024	***	-0.8534	
Lags: 11					
Commitment does not Granger Cause Product_5	2.35254	0.03111	**	0.635	
INCC does not Granger Cause Product_5	2.09065	0.0538	**	0.1766	x
SELIC does not Granger Cause Product_5	1.88382	0.08297	*	0.7172	
Commitment does not Granger Cause Product_6	2.09638	0.05315	**	0.5709	
INCC does not Granger Cause Product_6	2.07311	0.05581	**	0.2346	x
INCC does not Granger Cause Product_1	1.90770	0.07893	*	0.2708	x
IPCA does not Granger Cause Product_2	2.51964	0.02199	**	-0.3637	x
Commitment does not Granger Cause Product_4	2.43103	0.02642	**	0.2659	x
Unemployment does not Granger Cause Product_4	4.88082	0.00026	***	-0.8636	
IBC_BR does not Granger Cause Product_4	1.91677	0.07745	*	0.659	
SELIC does not Granger Cause Product_4	2.86417	0.01087	***	-0.1028	x

Lags: 10					
Commitment does not Granger Cause Product_5	2.85931	0.01115	***	0.6088	
Unemployment does not Granger Cause Product_5	2.09752	0.05378	**	-0.222	x
INCC does not Granger Cause Product_5	2.71047	0.0151	***	0.0512	x
SELIC does not Granger Cause Product_5	2.61376	0.01842	***	0.7097	
INCC does not Granger Cause Product_6	2.34281	0.03227	**	0.1824	x
Unemployment does not Granger Cause Product_2	1.87329	0.08572	*	0.4201	
IPCA does not Granger Cause Product_2	2.64372	0.01732	***	-0.263	x
Unemployment does not Granger Cause Product_4	5.74464	0.00006	***	-0.8685	
SELIC does not Granger Cause Product_4	2.41678	0.02768	**	-0.0125	x
Lags: 9					
Unemployment does not Granger Cause Product_4	2.93512	0.01022	***	-0.8676	
IBC_BR does not Granger Cause Product _2	1.96292	0.0736	*	-0.1468	x
INCC does not Granger Cause Product _6	2.10258	0.05538	**	0.1793	x
IPCA does not Granger Cause Product _2	3.01517	0.00871	***	-0.3423	x
SELIC does not Granger Cause Product _5	2.03970	0.06295	*	0.6959	
Lags: 8					
Unemployment does not Granger Cause Product _4	3.00471	0.01003	***	-0.8623	
INCC does not Granger Cause Product _6	2.49258	0.02735	**	0.2251	x
IPCA does not Granger Cause Product _2	2.25057	0.04408	**	-0.6278	
Lags: 7					
Commitment does not Granger Cause Product _3	1.95261	0.08501	*	0.7199	
Unemployment does not Granger Cause Product _5	1.88314	0.09668	*	-0.129	x
Unemployment does not Granger Cause Product _4	3.12684	0.00949	***	-0.864	
INCC does not Granger Cause Product _6	2.91510	0.01406	***	0.2277	x
INCC does not Granger Cause Product _1	1.87778	0.09764	*	-0.0054	x
INCC does not Granger Cause Product _4	1.86414	0.10013	*	0.1375	x
IPCA does not Granger Cause Product _2	2.29108	0.04519	**	-0.6388	
Lags: 6					
UNEMPLOYMENT does not Granger Cause PRODUCT_5	2.26743	0.0537	**	-0.074	x
INCC does not Granger Cause Product _6	3.39118	0.00761	***	0.2272	x
INCC does not Granger Cause Product _1	1.95892	0.0918	*	-0.0215	x
INCC does not Granger Cause Product _4	1.88374	0.10451	*	0.1578	x
Lags: 5					
Unemployment does not Granger Cause Product _5	1.98124	0.09842	*	-0.0089	x
INCC does not Granger Cause Product_6	1.91971	0.10842	*	0.1578	x
INCC does not Granger Cause Product _1	2.13879	0.07673	*	0.0752	x
INCC does not Granger Cause Product _4	2.62862	0.03523	**	0.1565	x
IPCA does not Granger Cause Product _2	2.10762	0.08061	*	-0.5112	
SELIC does not Granger Cause Product _4	2.21355	0.06816	*	0.3815	
Lags: 4					
INCC does not Granger Cause Product _4	2.36595	0.06503	*	0.2007	x
IPCA does not Granger Cause Product _2	2.04150	0.1024	*	-0.4863	
SELIC does not Granger Cause Product _6	2.15489	0.0874	*	0.6776	
SELIC does not Granger Cause Product _3	2.11648	0.09222	*	0.7334	
Lags: 3					
Commitment does not Granger Cause Product_3	3.41522	0.02369	**	0.6323	
IBC_BR does not Granger Cause Product_4	2.32101	0.08547	*	0.4443	
INCC does not Granger Cause Product_4	2.81564	0.04771	**	0.2329	x
SELIC does not Granger Cause Product_6	2.56818	0.06384	*	0.7168	
SELIC does not Granger Cause Product_3	3.87601	0.01393	***	0.7142	

SELIC does not Granger Cause Product_4	2.55591	0.06477	*	0.5111	
Lags: 2					
Commitment does not Granger Cause Product_3	2.61864	0.08166	*	0.5969	
Unemployment does not Granger Cause Product_1	2.81453	0.06828	*	-0.8417	
IBC_BR does not Granger Cause Product_6	2.32904	0.10659	*	0.2528	x
IBC_BR does not Granger Cause Product_4	3.79302	0.02841	**	0.409	
INCC does not Granger Cause Product_1	2.58639	0.08411	*	0.3571	
SELIC does not Granger Cause Product_5	2.61923	0.08161	*	0.5528	
SELIC does not Granger Cause Product_3	4.37103	0.01714	***	0.691	
SELIC does not Granger Cause Product_4	3.02012	0.05667	**	0.558	
Lags: 1					
Commitment does not Granger Cause Product_3	3.54761	0.06448	*	0.5494	
Unemployment does not Granger Cause Product_6	2.90435	0.09351	*	-0.6861	
IBC_BR does not Granger Cause Product_6	4.87150	0.03114	**	0.1646	x
IBC_BR does not Granger Cause Product_4	4.92552	0.03025	**	0.3499	x
SELIC does not Granger Cause Product_5	5.29016	0.02494	**	0.5464	
SELIC does not Granger Cause Product_3	4.31889	0.04198	**	0.6305	

Note: *, **, *** indicates rejection at 10%, 5% and 1% respectively.

Appendix-A3. Summary of R^2 for the main tested models.

Model	Product_3	Product_5	Product_4	Product_6	Product_1	Product_2
1	0.263919	0.108080	-0.033515	-0.002325	-0.074365	0.015099
2	0.553621	0.369507	-0.072506	0,452407	-0.112426	0.177935
3	0.545384	0.404728	0.033814	0,537862	-0.198120	0.234905
4	0.662559	0.218461	-0.018661	0,509705	-0.066339	0.288839
5	0.587517	0.413969	-0.062922	0,479561	-0.118926	0.189035
6	0.583961	0.426859	0.009940	0,485481	-0.146984	0.256103
7	0.693031	0.089861	-0.018288	0,504630	0.009759	0.340428
8	0.599644	0.411062	0.010056	0,503251	-0.204144	0.228217
9	0.594396	0.404644	-0.008569	0,518451	-0.177856	0.244977
10	0.692428	0.202599	-0.023773	0,506033	-0.077897	0.278787
11	0.365117	0.689601	0.182749	0,265197	0.156040	-0.112389
12	0.308629	-0.164239	0.351633	0,295347	0.233290	0.148636
13	0.162229	-0.208902	-0.014160	0,770779	0.180256	-0.287411
14	0.158904	0.058399	-0.074080	-0.015429	0.136451	0.099874
15	0.429491	0.017931	-0.074347	-0.061144	0.149139	0.441816
16	0.533226	0.586322	0.096788	0,469883	-0.148683	0.127934
17	0.584882	-0.346042	0.679820	0,467536	0.471830	0.174919
18	0.581231	-0.098167	0.701913	0,439166	0.468995	0.190192
19	0.700775	0.041935	0,693750	0.440150	0.427793	0.407863
20	0.709695	0.226806	0,712250	0.448960	0.342823	0.463414
21	0.727509	0.361516	0,686152	0.450076	0.313476	0.447152
22	0.716405	0.461197	0.693806	0.475194	0.308416	0.442064
23	0.758611	0.561243	0.655976	0.578099	0.272957	0.336448
24	0.793155	0.412395	0.608298	0.723063	0.219242	0.252011
25	0.721274	0.512322	0.64548	0.512516	0.28511	0.368687
26	0.801043	0.441008	0.583213	0.733547	0.172518	0.317909
27	0.793728	0.553039	0.605502	0.548709	0.232086	0.350131
28	0.773507	0.531833	0.64318	0.510297	0.301193	0.34659
29	0.743867	0.372999	0.641374	0.69131	0.26859	0.318475

30	0.815691	0.384267	0.592398	0.636511	0.236123	0.351135
31	0.819761	0.390834	0.543273	0.66192	0.231984	0.341166

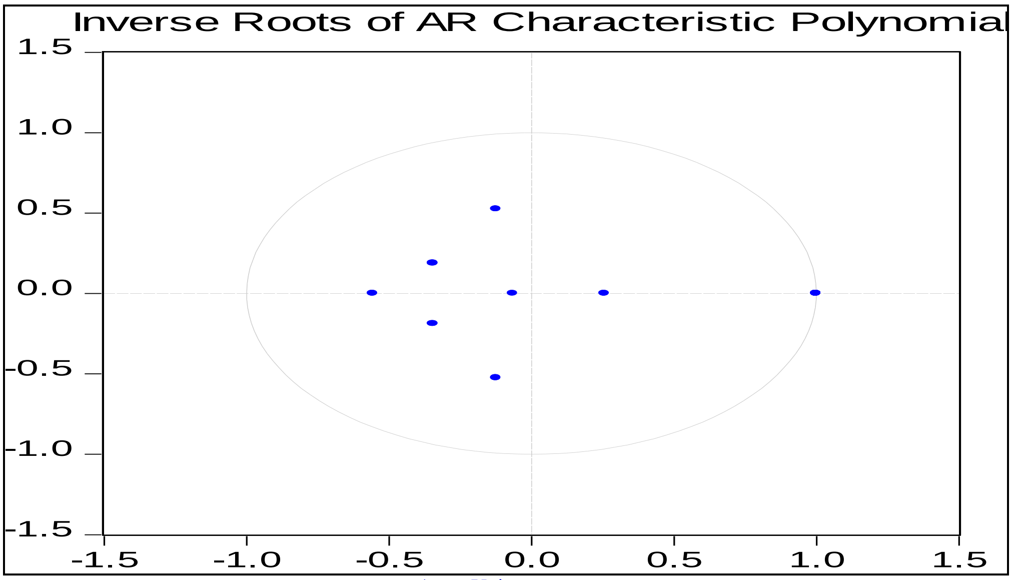
Appendix-A4. Final VEC model coefficients.

Vector error correction estimates						
Error Correction:	**D(Prod_3)**	**D(Prod_5)**	**D(Prod_4)**	**D(Prod_6)**	**D(Prod_1)**	**D(Prod_2)**
Cointeq1	0.174846	-1.265368	-0.005491	-0.222615	-0.845725	-0.810111
	(0.08359)	(0.17208)	(0.00415)	(0.09370)	(0.40232)	(0.59489)
	[2.09174]	[-7.35337]	[-1.32390]	[-2.37594]	[-2.10211]	[-1.36179]
D(Prod_3(-1))	-0.613435	0.699090	-0.000533	0.230657	-0.150418	0.005737
	(0.09413)	(0.19378)	(0.00467)	(0.10551)	(0.45305)	(0.66989)
	[-6.51706]	[3.60773]	[-0.11416]	[2.18615]	[-0.33202]	[0.00856]
D(Prod_5(-1))	-0.113936	-0.024436	-0.009093	0.128234	0.194932	0.528037
	(0.06503)	(0.13388)	(0.00323)	(0.07290)	(0.31301)	(0.46283)
	[-1.75196]	[-0.18252]	[-2.81793]	[1.75912]	[0.62276]	[1.14088]
D(Prod_4(-1))	5.136314	-13.38806	0.000136	-0.821758	-9.385877	-22.5598
	(2.45745)	(5.05903)	(0.12193)	(2.75458)	(11.8280)	(17.4892)
	[2.09010]	[-2.64637]	[0.00112]	[-0.29832]	[-0.79353]	[-1.28992]
D(Prod_6(-1))	-0.012217	0.794922	0.015830	-0.252615	1.001390	1.158347
	(0.15129)	(0.31145)	(0.00751)	(0.16958)	(0.72818)	(1.07671)
	[-0.08075]	[2.55229]	[2.10882]	[-1.48962]	[1.37520]	[1.07582]
D(Prod_1(-1))	-0.068658	0.359862	-0.001172	-0.007195	0.061312	0.348372
	(0.03943)	(0.08118)	(0.00196)	(0.04420)	(0.18980)	(0.28065)
	[-1.74107]	[4.43283]	[-0.59902]	[-0.16277]	[0.32303]	[1.24132]
D(Prod_2(-1))	0.075662	-0.148205	0.002657	-0.069532	-0.25064	-0.346004
	(0.02766)	(0.05694)	(0.00137)	(0.03100)	(0.13312)	(0.19684)
	[2.73563]	[-2.60293]	[1.93585]	[-2.24284]	[-1.88281]	[-1.75783]
C	0.124027	-0.148664	0.000480	-0.20109	0.974396	0.049136
	(0.11130)	(0.22912)	(0.00552)	(0.12475)	(0.53568)	(0.79207)
	[1.11439]	[-0.64885]	[0.08698]	[-1.61191]	[1.81899]	[0.06203]
Dummy_Prod3 _Outliers	0.031185	-0.0165	4.49E-05	-0.007873	0.027857	0.004790
	(0.00328)	(0.00676)	(0.00016)	(0.00368)	(0.01579)	(0.02335)
	[9.50316]	[-2.44243]	[0.27579]	[-2.14048]	[1.76374]	[0.20508]
Dummy_Prod5	0.003321	0.019310	0.000607	-0.002311	0.007868	0.000651
	(0.00260)	(0.00536)	(0.00013)	(0.00292)	(0.01253)	(0.01853)
	[1.27530]	[3.60231]	[4.69512]	[-0.79190]	[0.62779]	[0.03515]
Dummy_Prod6_1	-0.026857	0.019831	-0.000228	0.004259	0.018646	0.132738
	(0.00534)	(0.01099)	(0.00026)	(0.00598)	(0.02570)	(0.03799)
	[-5.03063]	[1.80444]	[-0.86247]	[0.71166]	[0.72565]	[3.49366]
Dummy_Prod2	0.001131	-0.01069	-0.00041	-0.001566	-0.01072	0.059715
	(0.00268)	(0.00552)	(0.00013)	(0.00301)	(0.01291)	(0.01909)
	[0.42180]	[-1.93632]	[-3.08068]	[-0.52084]	[-0.83057]	[3.12889]
Selic(-2)	-0.045533	0.032212	-0.000145	-0.019162	0.029355	0.137740
	(0.01629)	(0.03354)	(0.00081)	(0.01826)	(0.07842)	(0.11595)
	[-2.79479]	[0.96041]	[-0.17943]	[-1.04929]	[0.37435]	[1.18794]
Selic(-3)	-0.020166	0.059806	0.000354	-0.050277	0.186585	0.050886
	(0.01891)	(0.03893)	(0.00094)	(0.02120)	(0.09103)	(0.13460)
	[-1.06628]	[1.53609]	[0.37713]	[-2.37164]	[2.04977]	[0.37806]
Selic(-4)	-0.003389	0.020179	0.000905	-0.041015	-0.010434	0.062730
	(0.01413)	(0.02910)	(0.00070)	(0.01584)	(0.06803)	(0.10059)

	[-0.23976]	[0.69350]	[1.29089]	[-2.58882]	[-0.15337]	[0.62361]
Commitment (-11)	-0.003131	0.001499	0.000363	0.019779	-0.029473	-0.082745
	(0.00430)	(0.00884)	(0.00021)	(0.00481)	(0.02067)	(0.03057)
	[-0.72901]	[0.16949]	[1.70284]	[4.10801]	[-1.42563]	[-2.70682]
Commitment (-12)	0.006163	0.008174	-0.000415	-0.005142	0.020786	0.059993
	(0.00468)	(0.00963)	(0.00023)	(0.00524)	(0.02251)	(0.03328)
	[1.31785]	[0.84898]	[-1.79000]	[-0.98094]	[0.92343]	[1.80246]
Unemployment	1.758890	-1.168913	0.054509	-0.407961	-3.294843	1.998973
	(0.53711)	(1.10571)	(0.02665)	(0.60205)	(2.58514)	(3.82248)
	[3.27476]	[-1.05716]	[2.04537]	[-0.67763]	[-1.27453]	[0.52295]
Unemployment(-1)	-1.676941	1.358078	-0.074612	1.526001	1.416496	-3.076764
	(0.49536)	(1.01977)	(0.02458)	(0.55525)	(2.38421)	(3.52538)
	[-3.38530]	[1.33175]	[-3.03567]	[2.74830]	[0.59411]	[-0.87275]
Unemployment(-8)	0.385437	-0.060445	0.117498	1.345841	3.612389	-4.282182
	(0.49215)	(1.01317)	(0.02442)	(0.55166)	(2.36879)	(3.50257)
	[0.78316]	[-0.05966]	[4.81167]	[2.43962]	[1.52499]	[-1.22258]
Unemployment(-9)	-0.954121	0.725235	-0.137865	-2.223548	-5.877158	8.937701
	(0.68547)	(1.41115)	(0.03401)	(0.76835)	(3.29926)	(4.87839)
	[-1.39191]	[0.51393]	[-4.05347]	[-2.89391]	[-1.78136]	[1.83210]
Unemployment(-11)	-0.599242	-1.115471	0.062230	1.462732	4.018304	-12.56422
	(0.61137)	(1.25860)	(0.03033)	(0.68529)	(2.94259)	(4.35102)
	[-0.98016]	[-0.88628]	[2.05146]	[2.13447]	[1.36557]	[-2.88765]
Unemployment(-12)	0.277386	-0.302648	-0.023184	-2.253196	-0.364351	10.90308
	(0.58406)	(1.20237)	(0.02898)	(0.65468)	(2.81113)	(4.15663)
	[0.47493]	[-0.25171]	[-0.80002]	[-3.44170]	[-0.12961]	[2.62306]
Ibc_Br(-1)	-0,006523	-0,051216	0,003483	0,010748	-0,252557	-0,110796
	(0,03251)	(0,06692)	(0,00161)	(0,03644)	(0,15647)	(0,23136)
	[-0.20064]	[-0.76528]	[2.15947]	[0.29497]	[-1.61410]	[-0.47889]
Ibc_Br(-3)	-0,022893	-0,034689	-0,003739	0,007591	-0,4013	0,110166
	(0,03636)	(0,0785)	(0,00180)	(0,04075)	(0,175)	(0,25876)
	[-0.62965]	[-0.46345]	[-2.07272]	[0.18627]	[-2.29319]	[0.42575]
Ipca(-4)	-0.000275	0.005102	0.000189	-0.0078	-0.009497	-0.014265
	(0.00282)	(0.00581)	(0.00014)	(0.00316)	(0.01358)	(0.02008)
	[-0.09738]	[0.87813]	[1.35066]	[-2.46554]	[-0.69919]	[-0.71024]
Ipca(-5)	-0.002166	0.008482	0.000344	0.000500	-0.011577	-0.022727
	(0.00296)	(0.00610)	(0.00015)	(0.00332)	(0.01425)	(0.02107)
	[-0.73138]	[1.39138]	[2.33964]	[0.15060]	[-0.81226]	[-1.07843]
Dummy_Ibc	-0.032116	0.022031	-0.000121	-0.005857	0.055405	0.116855
	(0.00714)	(0.01470)	(0.00035)	(0.00801)	(0.03437)	(0.05083)
	[-4.49681]	[1.49844]	[-0.34158]	[-0.73166]	[1.61178]	[2.29904]
R-squared	0.886405	0.793526	0.838106	0.801458	0.657862	0.687740
Adj. R-squared	0.758611	0.561243	0.655976	0.578099	0.272957	0.336448

Note: Standard errors in ( ) & t-statistics in [ ].

Appendix-A5. Unit root, Residual normality, Serial correlation, and Heteroskedasticity Tests.

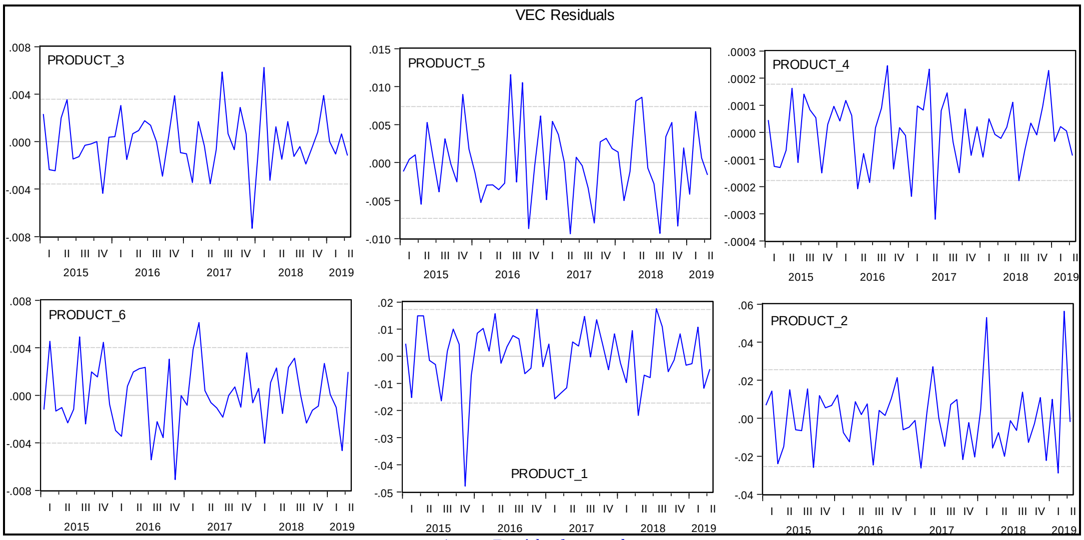


A5.1. Unit root test.

A-52. Residual normality test.

VEC residual normality tests								
Orthogonalization: Cholesky (Lutkepohl)								
Component	**Skewness**	**Chi-sq**	**Prob.**	**Kurtosis**	**Chi-sq**	**Prob.**	**Jarque-Bera**	**Prob.**
1	0.036157	0.011330	0.9152	4.063830	2.452092	0.1174	2.463423	0.2918
2	0.151445	0.198776	0.6557	2.776458	0.108270	0.7421	0.307046	0.8577
3	0.178935	0.277487	0.5984	2.363094	0.878908	0.3485	1.156395	0.5609
4	0.266869	0.617230	0.4321	2.869367	0.036974	0.8475	0.654204	0.7210
5	-0.770501	5.145159	0.0233	4.610636	5.620657	0.0177	10.76582	0.0046
6	0.056195	0.027368	0.8686	2.400729	0.778105	0.3777	0.805473	0.6685
Joint		6.277350	0.3928		9.875006	0.1300	16.15236	0.1844

Note: Null Hypothesis: Residuals are multivariate normal.



A5.3. Residuals graphs.

A5-4. Residuals serial correlation test.

VEC residual serial correlation LM tests						
Lag	**LRE* stat**	**df**	**Prob.**	**Rao F-stat**	**df**	**Prob.**
1	28.09014	36	0.8240	0.733596	(36, 59.8)	0.8397

Note: Null Hypothesis: There is no serial correlation in the residuals up to the specified order.

A5.5. Residual Heteroskedasticity test.

VEC residual heteroskedasticity tests (Levels and Squares)					
Joint test:		**Chi-sq**	**df**	**Prob.**	
		1039.045	**1029**	**0.4070**	
Individual components:					
Dependent	**R-squared**	**F(49,2)**	**Prob.**	**Chi-sq(49)**	**Prob.**
res1*res1	0.996601	11.96600	0.0800	51.82323	0.3643
res2*res2	0.912924	0.427929	0.8927	47.47206	0.5352
res3*res3	0.998317	24.21051	0.0404	51.91248	0.3611
res4*res4	0.900095	0.367737	0.9241	46.80496	0.5626
res5*res5	0.947422	0.735484	0.7337	49.26594	0.4625
res6*res6	0.937673	0.614057	0.7933	48.75899	0.4828
res2*res1	0.996874	13.01718	0.0738	51.83746	0.3638
res3*res1	0.991435	4.724403	0.1900	51.55460	0.3742
res3*res2	0.988880	3.629712	0.2396	51.42176	0.3791
res4*res1	0.969652	1.304123	0.5300	50.42190	0.4170
res4*res2	0.980422	2.043973	0.3839	50.98194	0.3956
res4*res3	0.782538	0.146877	0.9975	40.69196	0.7949
res5*res1	0.996989	13.51648	0.0712	51.84345	0.3636
res5*res2	0.917416	0.453422	0.8790	47.70561	0.5257
res5*res3	0.980507	2.053076	0.3826	50.98636	0.3954
res5*res4	0.929013	0.534163	0.8354	48.30865	0.5011
res6*res1	0.998627	29.69663	0.0331	51.92863	0.3605
res6*res2	0.900595	0.369788	0.9231	46.83092	0.5615
res6*res3	0.944905	0.700025	0.7505	49.13508	0.4677
res6*res4	0.962554	1.049186	0.6074	50.05280	0.4314
res6*res5	0.986885	3.071395	0.2763	51.31803	0.3830

Note: Null Hypothesis: The variances for the errors are equal (homoscedasticity).

Appendix-A6. Trace and Maximum Eigenvalue tests for cointegration (final model, third specification of the deterministic function).

Unrestricted Cointegration Rank Test (Trace)				
Hypothesized No. Of CE(s)	**Eigenvalue**	**Trace Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.939393	407.2759	95.75366	0.0001
At most 1 *	0.907670	261.5022	69.81889	0.0000
At most 2 *	0.654249	137.6179	47.85613	0.0000
At most 3 *	0.598016	82.39197	29.79707	0.0000
At most 4 *	0.443962	35.00218	15.49471	0.0000
At most 5 *	0.082590	4.482460	3.841466	0.0342
Trace test indicates 6 cointegrating eqn(s) at the 0.05 level				
Unrestricted Cointegration Rank Test (Maximum Eigenvalue)				
Hypothesized No. Of CE(s)	**Eigenvalue**	**Max-Eigen Statistic**	**0.05 Critical Value**	**Prob.****
None *	0.939393	145.7736	40.07757	0.0001
At most 1 *	0.907670	123.8843	33.87687	0.0000
At most 2 *	0.654249	55.22596	27.58434	0.0000
At most 3 *	0.598016	47.38978	21.13162	0.0000
At most 4 *	0.443962	30.51972	14.26460	0.0001
At most 5 *	0.082590	4.482460	3.841466	0.0342

Note: Max-eigenvalue test indicates 6 cointegrating eqn(s) at the 0.05 level.
*denotes rejection of the hypothesis at the 0.05 level.

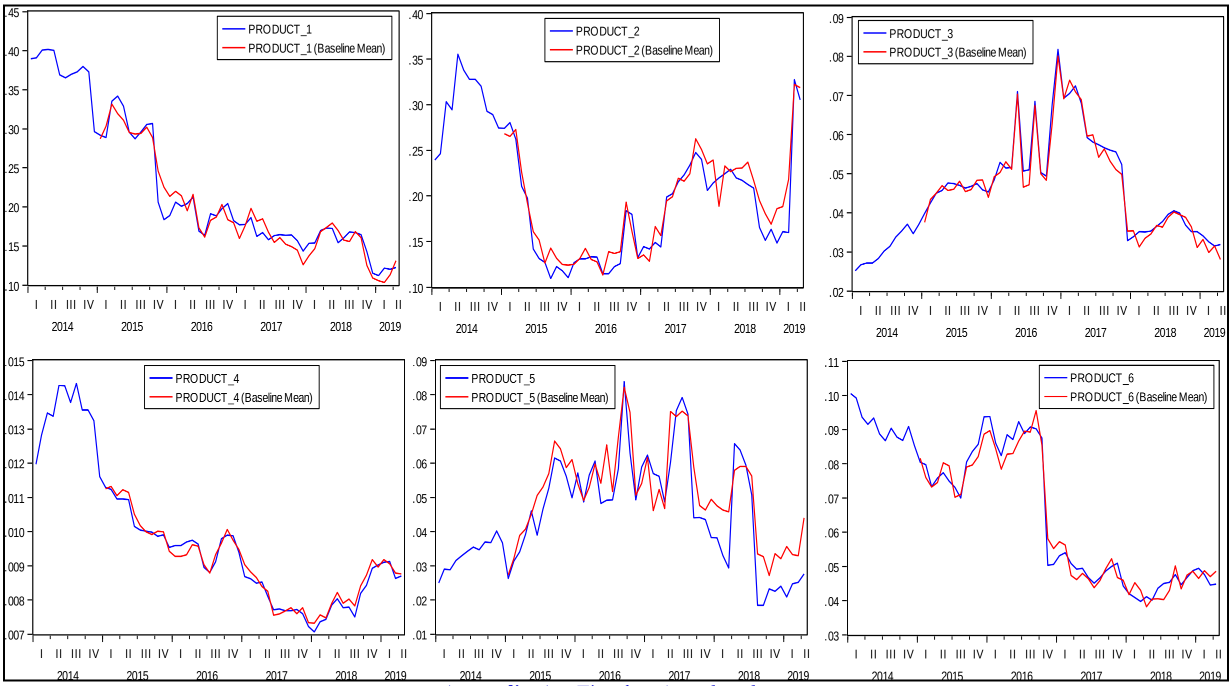
**MacKinnon et al. (1999) p-values.

Appendix-A7. – Normalized cointegrating vectors.

Variables:	Product_3	Product_5	Product_4	Product_6	Product_1	Product_2
Vector	1.000000	0.584336	-7.530396	1.585087	0.324901	-0.040617
Standard errors		0.043920	2.030690	0.128870	0.039690	0.022680

Appendix-A8. Speed of adjustment coefficients.

Variable	Unrestricted adjustment coefficients (alpha)					
D(Product_3)	-0.001038	0.001144	0.000401	0.000644	0.001042	-0.000288
D(Product_5)	0.007509	0.000320	0.002940	-0.001933	-0.000842	-0.000133
D(Product_4)	3.26E-05	3.80E-05	-1.67E-06	-5.99E-05	5.23E-06	-2.37E-05
D(Product_6)	0.001321	-0.00241	-8.79E-05	-0.000161	0.000608	-3.92E-05
D(Product_1)	0.005018	0.003170	-0.002664	0.007065	-0.003032	-0.000866
D(Product_2)	0.004807	0.007451	-0.0054	-0.000971	0.005903	0.003038



Appendix-A9. Fitted vs Actuals values.

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