Significance Validation Test of the Lipstick Effect in Brazil During 1989 - 2016

Abstract

Economists have observed that during economic downturns, sales of certain "inferior goods," such as lipstick, increase compared to most goods whose sales decline due to a decrease in consumer income. This phenomenon is known as the "lipstick effect" in economics. However, the lipstick effect lacks empirical verification of its generalizability, and although a 2019 report suggests that the existence of the lipstick effect was first confirmed by examining U.S. retail cosmetics data from 2006-2016, we have doubts about its validity across cultural contexts and economic conditions. Therefore, we analyzed data on the value of cosmetics imports in Brazil for the period 1989-2016 using Time Series Analysis and Generalized Additive Models (GAMs) to verify whether the lipstick effect is regionally significant in Brazil. Our findings are that even though the value of total Brazilian imports and the value of Brazilian cosmetics imports are inversely correlated in some specific years, the coefficients are too small to be significant. Therefore, we conclude that the lipstick effect is not significantly present in Brazil from 1989-2016.

Keywords: Economy, Time Series Analysis, General Additive Model

1 Introduction

In the consumer choice theory, the effect of a change in the price of a good on consumption can be broken down into two effects: the income effect and the substitution effect. Generally speaking, when the economic environment is harsh and people's income decreases, if the price of a good stays the same, the sale of that good should decrease. This is the income-effect.[1] However, in fact, many scholars have found that during economic recessions, sales of certain goods (e.g., lipstick) tend to increase. Such a strange phenomenon is called the "lipstick effect".

The "lipstick effect" economic theory, also known as the "low-price product preference trend," first proposed in the 1930s during the Great Depression in the United States, refers to an interesting macroeconomic phenomenon, that lipstick sales increase dramatically due to economic recession.[2] The definition of the lipstick effect is: "Whenever during an economic recession, the sales of cheap luxury goods would increase instead."

The macroeconomic explanation for this phenomenon is that in an economic recession, people's income decreases, and normally people's consumption decreases accordingly. However, when people give up the consumption of expensive goods such as houses, cars, and trips abroad, they will spend their spare money on the substitutes of those expensive goods - "(inferior goods)cheap and non-essential items." [3]Lipstick, as a "cheap, non-essential item," serves as a "comfort" to consumers. This substitution effect is far greater than the reduction in income and consumption, and thus the lipstick effect arises.

However there is an ongoing debate about the reliability and significance of the lipstick effect. *The Economist* tested the lipstick effect in 2009 through a statistical analysis by Data collected by Kline & Company, a market-research group, and concluded that there was "no significant correlation between lipstick sales and the economic recessions." Also *The Economist* notes that reliable historical lipstick sales data are hard to find, so "most lipstick believers can only point to isolated, anecdotal examples as evidence of the larger phenomenon."[4] Another article published in *Applied Economic* in 2019 notes that by analyzing weekly retail data on lipstick sales in the United States between 2006 and 2016, with Panel Smooth Transition Regression (PSTR) demand model to test the relationship between economic distress and lipstick sales. The authors "first empirically confirmed the existence of The lipstick effect." [5]

Therefore, we want to verify statistically whether it is true that people tend to consume cheap luxury goods whenever there is a recession by using data from different countries. Due to data collection constraints, we selected only Brazilian data in this study. The data we use comes from the Brazilian cosmetic imports collected by Quandl[6]. While the Brazilian Gross Domestic Production (GDP), Income, total imports were collected by the World Bank and IMF (International Monetary Fund)[7]. We wanted to examine the Brazilian data to verify whether the "lipstick effect" is regionally significant.

2 Project Description

2.1 Research Questions

Question 1: Is there a relationship between cosmetic import with the economic recession in Brazil?

Question 2: Do cosmetic imports rise when the Brazilian economy goes down?

2.2 Statistical Questions

Question 1: Is there a linear relationship between cosmetic imports and Gross Domestic Production (GDP) in Brazil?

Question 2: Is the change in Gross Domestic Production (GDP) a statistically significant variable for cosmetic imports?

2.3 Variables of Interest

We chose the Brazilian cosmetic imports as our response variable to measure the consumption of cosmetics in Brazil. And we chose the Brazilian total imports, Gross Domestic Production (GDP), and income per ca-pita as our explanatory variables to measure Brazil's economic environment. We also chose China's Gross Domestic Production (GDP) as a supplementary explanatory variable because China is a major economy in the production and export of cosmetics.

It is worth noting that Brazilian cosmetic imports are based on months, while the other variables are based on years, as we were unable to collect more detailed data. Thus, we sum up the monthly cosmetic imports value based on the annual circle. For the detailed data set description, please check Appendix A.

We further add an indicator variable, Recession, to denote whether Brazil is in a recession or not to help our audience understand the time period mentioned in the main text.

All units of the variable are based on current US dollars.

The importRatio is calculated by the formula:

$$\frac{BrazilCosmeticImport}{BrazilGoodImport}$$

Variables	Category	Description	Level
Year	integer	Year of data collected	1989 - 2016
Month	integer	Month of data collected	1 - 12
Value	integer	Cosmetic goods import value of Brazil	29921278 to 1268644077
BrazilgoodImport	floating	Total goods import value of Brazil	1.98850e+10 to 2.50556e+11
BrazilGDP	floating	Brazil's Gross Domestic Production (GDP)	4.00599e+11 to 2.61620e+12
ChinaGDP	floating	China's Gross Domestic Production (GDP)	3.47768e+11 to 1.12333e+13
BrailIncome	integer	Brazil's Income per ca-pita	2730 to 12790
importRatio	floating	Proportion of cosmetic goods import to total goods import value.	0.001504716 to 0.005483859
Recession	Logical	Indicator of Brazil recession	1991-1992 recession, 1997-1999 recession, 2000-2002 recession, 2011-2016 recession

Table 1: Variable of interest used in this research.

3 Exploratory Data Analysis (EDA)

Our data are reviewed, pre-processed, and merged with four data sets (See Appendix A for raw data description and analysis and data pre-processing producers). Our data contains seven variables, which are Year, cosmetic import value, good import value, Brazil Gross Domestic Production (GDP), China Gross Domestic Production (GDP), Brazil Income (per ca-pita) and a new calculated variable import Ratio. Our data contains twenty-eight records, which includes these seven variables from 1989-2016. There are no missing values in our data set.

The primary goal of this research is to focus on whether there is a relationship between cosmetic import with the economic recession in the Brazilian Market. We calculated that importRatio because lipstick effect does not mean people necessarily spend more money on cosmetics during the economic recession but higher percent of their money on cosmetics instead of other luxury products. Therefore, we involve the new calculated variable import Ratio in our investigation. Thus, we want first to examine the relationship between Year and our variables as the start point. First, we would like to see the summary statistics on our data set (See Table2) to provide us a big picture of how our variables associate with Years in general. In Table 2, we categorize a total of 28 years into three categories in approximately ten-year frames. To increase our summary table's readability, we use US dollars in billions as units instead of the US dollar for cosmetics import, good import, Brazil Gross Domestic Production (GDP), and China Gross Domestic Production (GDP).

	1989-1999 (N=11)	2000-2010 (N=10)	2011-2016 (N=7)	Overall (N=28)
Cosmetics Import ($ in Billion)				
Mean (SD)	0.125(0.0903)	0.320 (0.136)	1.01 (0.191)	0.416 (0.383)
Median[Min, Max]	0.0963[0.0299, 0.260]	0.258 [0.184, 0.543]	1.01 [0. 750, 1.27]	0.239 [0.0299, 1.27]
Good Import ($ in Billion)				
Mean (SD)	40.0 (17.6)	90.0 (44.3)	211 (39.8)	101 (76.1)
Median[Min, Max]	36.2 [19.9, 64.2]	72.0 [49.7, 182]	233 [143, 251]	62.4 [19.9, 251]
importRatio (Cos Imp/ Good Imp)				
Mean (SD)	0.00274 (0.00106)	0.00365 (0.000331)	0.00482 (0.000505)	0.00358 (0.00110)
Median[Min, Max]	0.00266 [0.00150, 0.00441]	0.00364 [0.00298, 0.00408]	0.00489 [0.00410, 0.00548]	0.00367 [0.00150, 0.00548]
Brazil GDP ($ in Billion)				
Mean (SD)	623 (188)	971 (467)	2260 (337)	1160 (745)
Median[Min, Max]	599 [401 , 883]	780 [508, 1700]	2460 [1800, 2620]	857 [401, 2620]
China GDP ($ in Billion)				
Mean (SD)	656 (289)	2590 (1390)	9220 (1920)	3490 (3680)
Median[Min, Max]	564 [348, 1090]	2120 [1210, 5100]	9570 [6090, 11200]	1570 [348, 11200]
Brazil Income ($ per capita)				
Mean (SD)	3660 (830)	4770 (1950)	11000 (1470)	5890 (3360)
Median[Min, Max]	3280 [2730, 5020]	3970 [2980, 8320]	111 00 [8920, 12800]	4290 [2730, 12800]

Table 2: A summary statistics table on our data set with units as US dollar in Billion.

An apparent increase between each ten-year frame on both Brazilian Cosmetics import and Brazilian Good Import is shown in Table 2. In the meantime, the import ratio tends to increase as well. Notably, the increase in import ratio between 2000-2010 and 2011-2016 is more considerable than the import ratio between 1989-1999 and 2000-2010, the same on both Cosmetics Import and Good Import.

For both Brazil's Gross Domestic Production (GDP) and China's Gross Domestic Production (GDP), they increase positively, and China's GDP rises faster than that of Brazil. Nevertheless, Brazil's GDP is significantly associated with Brazil's Income per ca-pita. We can tell that they are almost entirely correlated at the same rate. To further investigate the correlations in our data, please see Appendix B, Figure B1, for further information.

After getting a big picture of the trends of our variables in Years in general, we want to take a closer look at Brazil's Gross Domestic Production (GDP) and Brazil's recession periods to deeply investigate our research question about if economic recession would influence the cosmetic import in Brazilian Market.

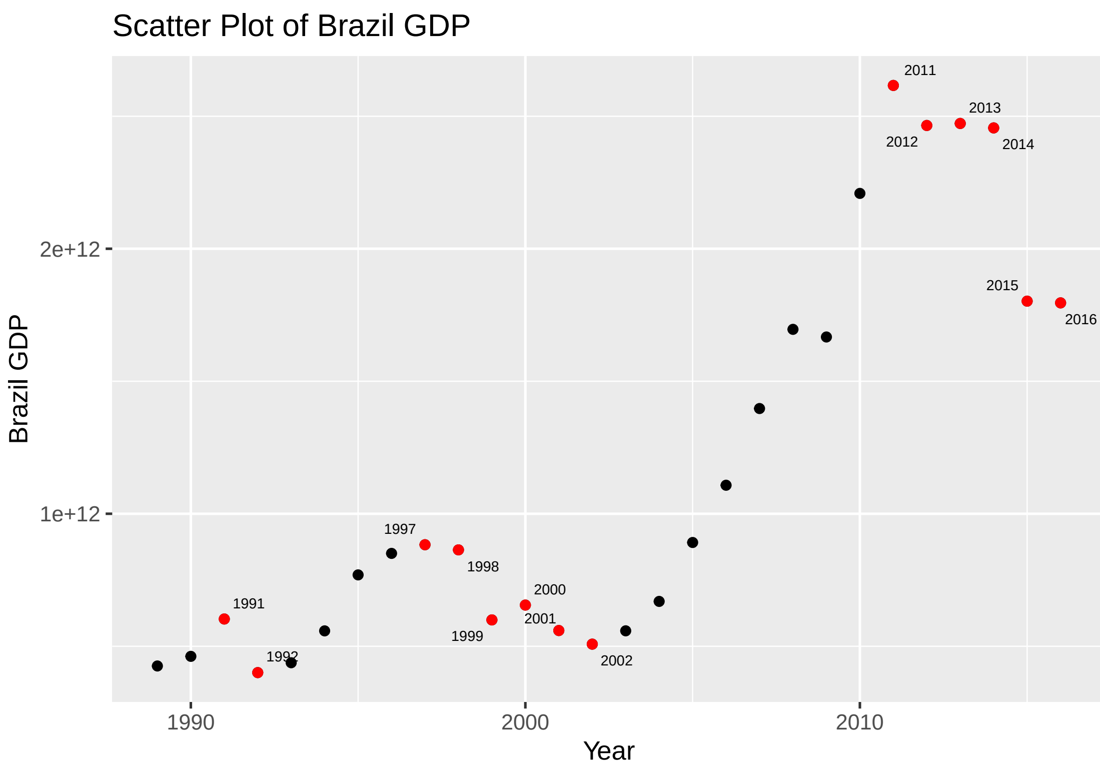

Figure 1: The trends of Brazil Gross Domestic Production (GDP) between 1989-2016 with recession years labeled.

There are both increasing and decreasing trends of Brazil Gross Domestic Production (GDP) during our responsive time frame (1989-2016) shown in Figure 1. We highlighted and labeled the years within downward trends with red color and considered them as potential recession years since we mainly focus on using Gross Domestic Production (GDP) to determine economic recession. As we can see from Figure 1, the period of 1991-1992, 1997-1999, 2000-2002, and 2011-2016 could be considered as recession years based on Brazil's Gross Domestic Production (GDP) trends. We would further discuss the possible explanations for these recession years in terms of economics or social events on our following statistical modeling part and conclusions. In addition, we would like to investigate the response of Brazilian cosmetics import data, good import data and the import ratio of cosmetics in the Brazilian market to recession years in the time frame of interest.

In Figure2, We can tell that both Brazil's cosmetics imports and Brazil's good imports have similar patterns as Brazil's Gross Domestic Production (GDP). While the trend of Cosmetics import has upwards then downwards during the recession period of 2011-2016, the trend of good import has mostly downwards during this period. On the other side, when we looked at the import ratio scatter plot, we can tell the trend went upwards during the recession period of 1997-1999 and 2011-2016, and downwards during the recession period of 1991-1992 and 2000-2002. We would further discuss the possible explanations in terms of potential economic and social causes and whether such situations can support the lipstick effect theory.

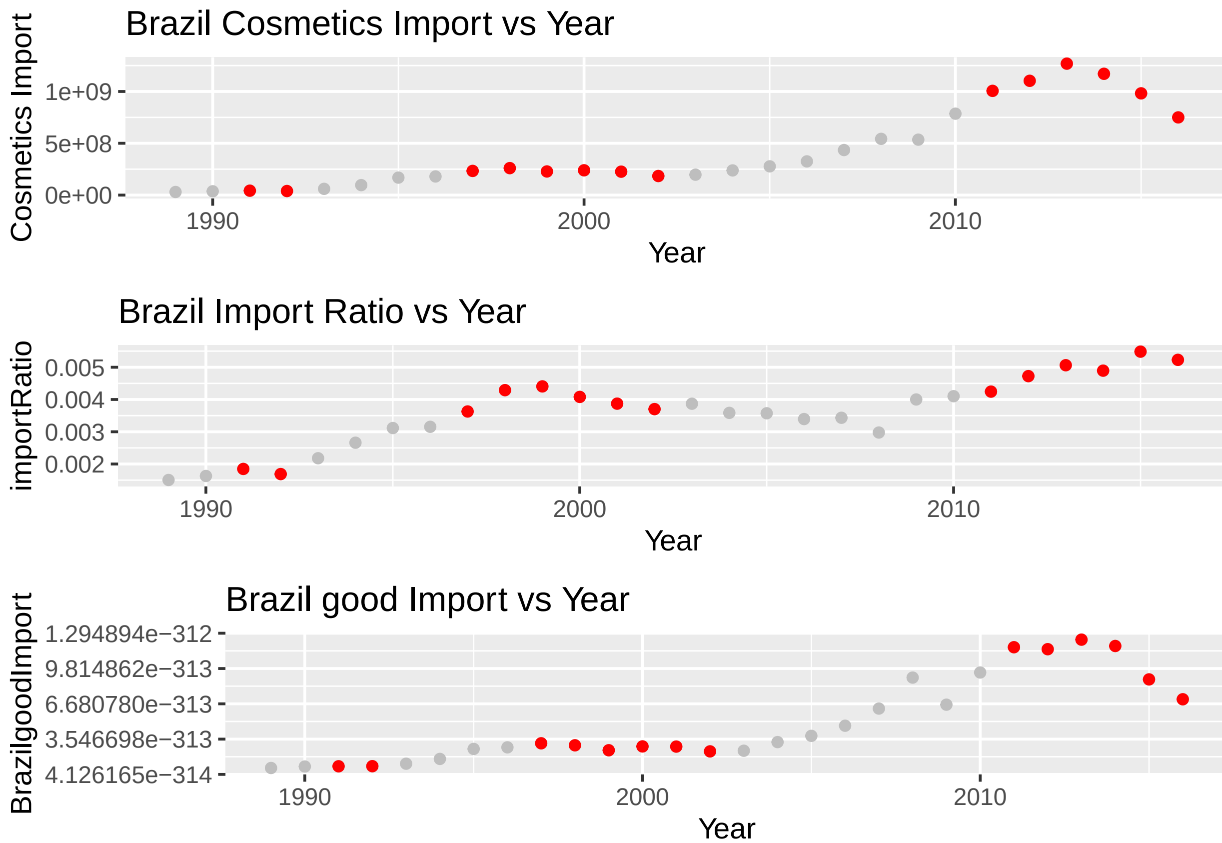

Figure 2: Regression plots on Brazil Cosmetics Import, Brazil Good Import and Brazil Import Ration in terms of Years between 1989-2016 with recession periods highlight in red.

4 Statistical Analysis

Answering the research question, we plan to predict the next few years' import value and the ratio of Brazil and compare with the real data set to see if they are matched. Then we can draw conclusions based on the next few years' Brazil Gross Domestic Production (GDP) trend and prediction model.

To start fitting the model to describe the trend of Brazil's import cosmetic value, time was considered as the explanatory variable, and the import cosmetic value(US dollar currency) was treated as the response variable. We use a generalized linear regression model to see the trend of the Brazil cosmetic import value time-series data (See Figure 3), which clearly shows that is an increasing trend meaning that the total import value of Brazil cosmetics increased.

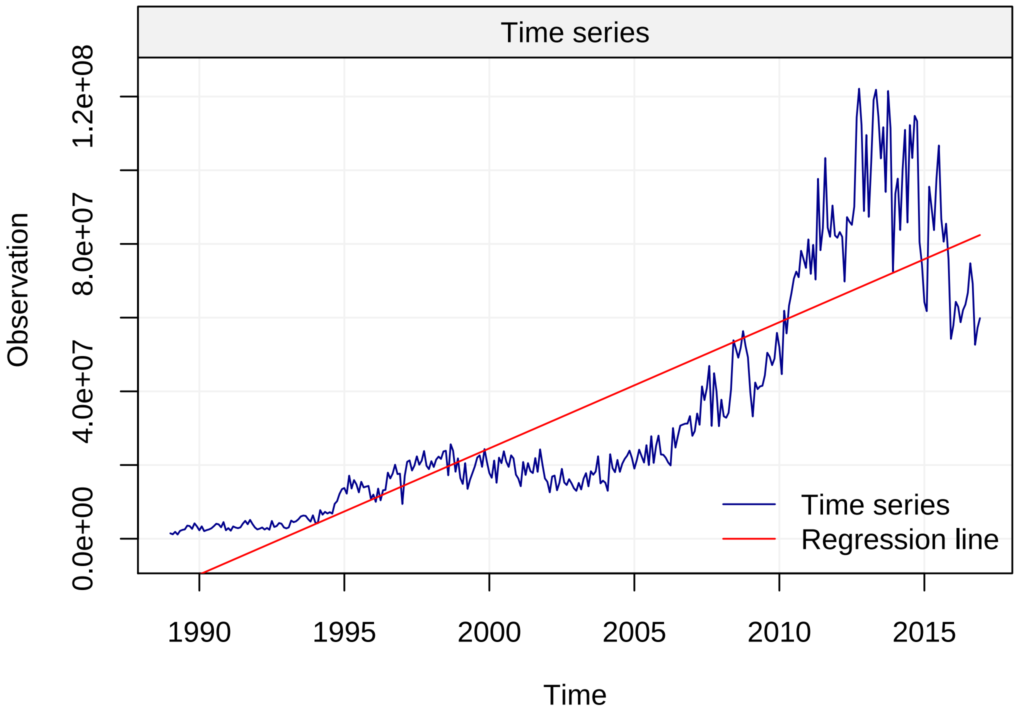

Figure 3: Time series plot with simple linear regression fitted, showing an upward trend, while it shows the regression line cannot perfectly fit the time-series data set.

However, as shown on the plot, generalized linear regression could not effectively fit the selected data since we assumed each data is independent in regression. In contrast, in time series, data are correlated with each other. Thus, we concluded that generalized linear regression is not ideal for real-time Brazil import cosmetic value. It can only be an auxiliary method to help us determine coefficients.

When facing series data, especially time as an indicator, we cannot use a regression model to predict. We will meet âusing the future to predict historyâ failure, leading to the model over-fit problem. Time series analysis solves this problem by assuming each data point may correlate with another by the time order. In specific, time series analysis accounts for the fact that the values of a variable are in an ordered sequence at equally spaced time intervals. Regarding the characteristics of the selected that each data point is indexed in time order, we applied time series analysis in our study. First, we try the AR(1) model (See Appendix C Table 1). The residuals plot shows it is not stationary though the histogram of the residuals seems normal. Normal Q-Q plot is not ideal that all points close to the line, also for the Ljung-Box Test Result as not all points above the horizontal line, it may indicate that AR(1) model is not the best fitting model. Similar results for MA(1) model (See Appendix C Table 2), with the same idea that residuals are not stationary. However, both their ACF and PACF plots show most of the lags fall into blue-shaded areas, suggesting we may consider the ARIMA model.

Before we use ARIMA, we de-trend yearly influence may distract real data, eliminating external factors to make a more accurate prediction. (See Appendix C Table 3) Within the basic de-trend method, we could only conclude that the import cosmetic value in Brazil will decrease in the next few years. In addition, we compose time series data and split it into four parts: observed, trend, seasonal, random. (See Appendix C, Figure 8).

With the KPSS unit root test, we eliminate white noise inside the random part, then with the new ACF plot (See Appendix C Figure 9), the auto-correlation continues to decrease as the lag increases, confirming that there is no linear association between observations separated by larger lags. After removing seasonal trends, both ACF and PACF plots (see Appendix C Figure 10) suggest we should try the ARIMA model with lag 5 or 6. We find ARIMA(3,1,3) has the lowest AIC scores in all possible models(See Appendix C Table 4). We double-check that within the auto.arima function in R, which also proved our finding. (See Appendix C Table 5). The final forecasting based on ARIMA(3,1,3) shows, which matched the real-time data. (See Figure 4)

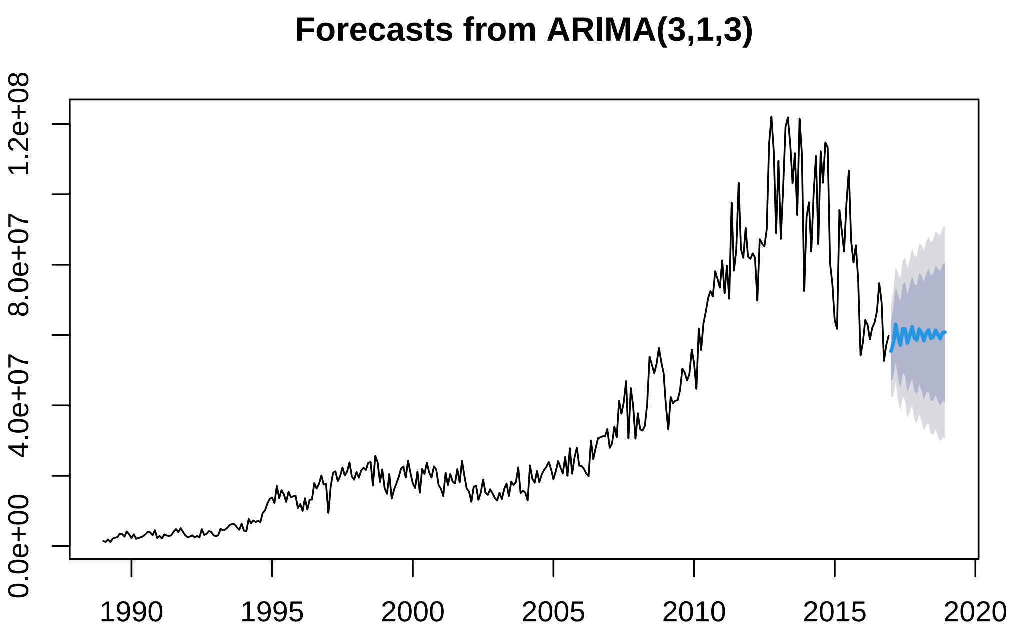

Figure 4: Forecasts on the import value of the next few years.

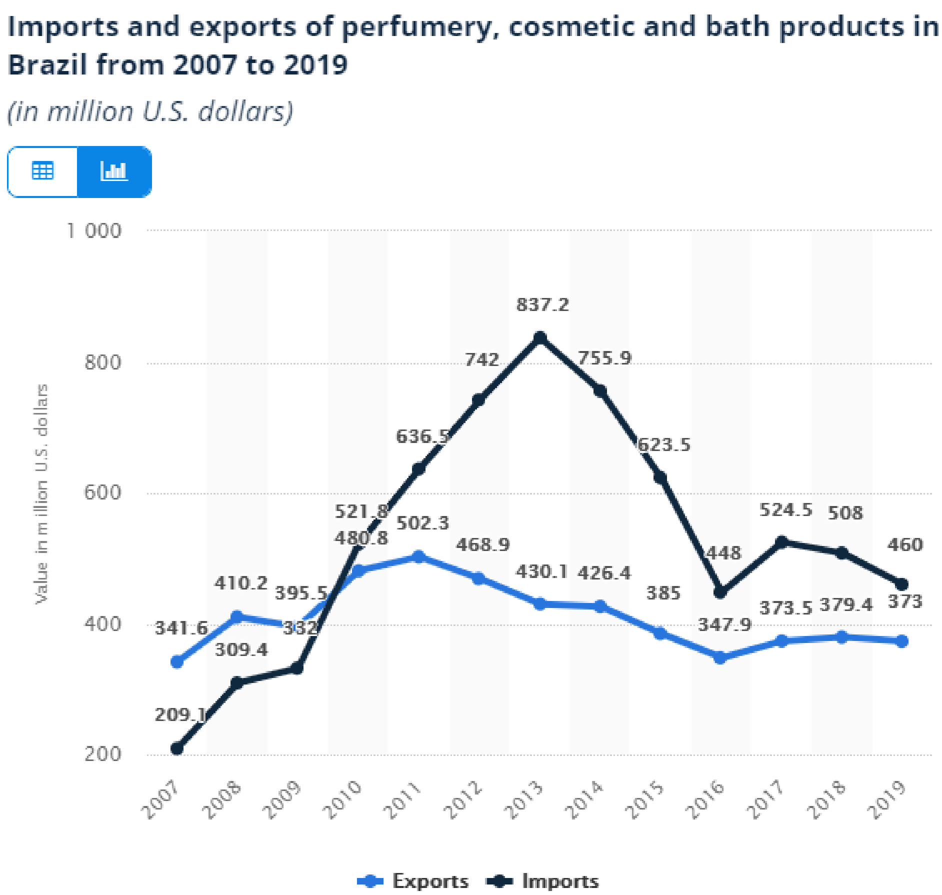

Figure 5: Figure 4 is the prediction of the Brazil import value in the next few years, especially for the blue line we can see it's sort of stationary. While Figure 5, especially for the dark line, represents the actual imports of perfumery, cosmetic products in Brazil. If we focus on the year after 2016, we can see it's also kind of stationary, as in 2019 the import value is very close to 2016. Which further proves our prediction by using ARIMA (3,1,3) is correct.

However, only the Time series prediction model is not enough. It can not give a direct correlation between Brazil's Gross Domestic Production (GDP) and cosmetic import value. Then we consider using the Generalized Additive Model(GAMs) to fit the time series data set but also can have a direct correlation helping with whether lipstick effects are correct in the Brazilian market. First of all, the nodes in the GAMs model, meaning a change point of variables, can be defined as whether the sign of a variable is changing or the rate of change. Besides, a cubic spline method is usually used when we want to fit a curve with a straight line but as smooth as possible. In our model, we regard each time period peak of Brazil's Gross Domestic Production (GDP) as a node. Then we use a cubic spline method with nodes equal to 5, which every time the sign of the first derivative of a function has changed we add one node. We used the import ratio (import value/total import value) as a response variable and we found it roughly showed it has a positive correlation with Brazil's average yearly income, while the negative correlation with Brazil's Gross Domestic Production (GDP) (See Appendix C figure 9) and both two explanatory variables have a significant influence on import ratio.

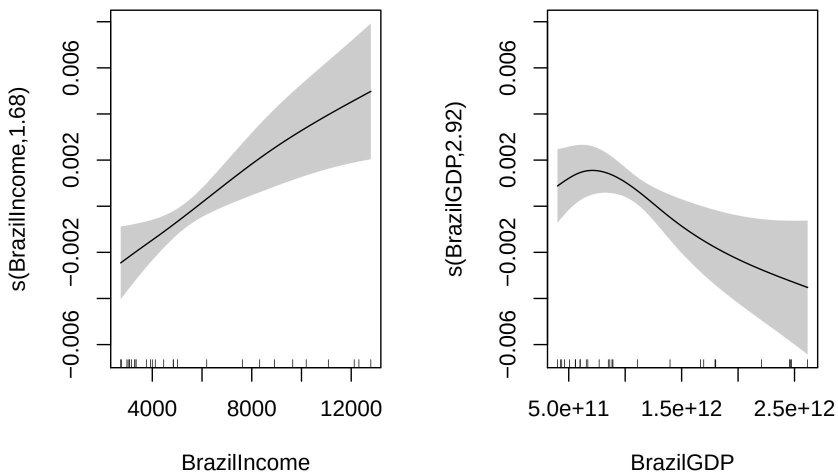

Figure 6: Generalized Additive Model with the trend of Brazil's income and Gross Domestic Production (GDP). While the left graph showing the BrazilIncome are consistently increasing, while the Brazil Gross Domestic Production (GDP) is first increasing that decreasing, make it possible for us to discuss lipstick effect.

In addition, with the natural splines method, we find only Brazil Income has significant influence with especially nodes 3,4,5. (See table 3 below) Which means, in the year 1997-2016 when income increase and import ratio of cosmetics also increased meaning that we reject the hypothesis that when economic recession people will spend more money on lipstick.

	Estimate	**p-value**
Intercept	0.0014267	0.00722
ns(BrazilIncome, df = 5) 1	0.0013728	0.15194
ns(BrazilIncome, df = 5) 2	0.0023122	0.22631
ns(BrazilIncome, df = 5) 3	0.0059164	0.04241
ns(BrazilIncome, df = 5) 4	0.0074698	0.01847
ns(BrazilIncome, df = 5) 5	0.0070031	0.01250
ns(BrazilGDP, df = 4) 1	**-0.0002218**	**0.87792**
ns(BrazilGDP, df = 4) 2	**-0.0027204**	**0.34213**
ns(BrazilGDP, df = 4) 3	**-0.0018800**	**0.51517**
ns(BrazilGDP, df = 4) 4	**-0.0050421**	**0.06062**

Table 3: The Generalized Additive Model model with natural splines detecting nodes 3-5 have significant influence, which further explained only the year after 2000 that income will significantly influence the import value and ratio. Besides, Brazil's Gross Domestic Production (GDP) after 2000 will have a significant influence on the import value and ratio.

5 Discussion and Conclusion

For our first statistical question, "Is there a linear relationship between cosmetic imports and Gross Domestic Production (GDP) in Brazil?". Based on our time series analysis, there is no linear relationship between these two variables. However, they do have a nonlinear relationship based on the ARIMA(3,1,3) model. In the following four years, Brazil's absolute import value of cosmetics is stationary while Brazil's Gross Domestic Production (GDP) goes up. This finding further suggests that people will at least spend the same amount of money on light luxury products such as cosmetic products when facing economic growth.

The time series prediction model also helped answer our second statistics question, "Do cosmetic imports rise when the Brazilian economy goes down?". We conclude that cosmetic imports will rise when the Brazilian economy also increases, even though they have a slightly negative correlation in specific years such as 1998, 2014. However, these correlations are also not significant.

Our primary research question is, "Is there a relationship between cosmetic import and the economic recession in Brazil?". Based on our analysis, especially for the Generalized Additive Model (GAM) model, we find a negative relationship between cosmetic import ratio with Brazil Gross Domestic Production (GDP), though it's not significant. We find it has a positive relationship between import ratio with Brazil Income and its significance, which indicates we need to reject the null hypothesis. And for our second research question, "Do cosmetic imports rise when the Brazilian economy goes down?". We don't have enough evidence to prove when an economic recession, like when Gross Domestic Production (GDP) decreases, people will spend more percentage of their funds on light luxury goods, especially for cosmetic products.

Thus, we need to conclude that the lipstick effect does not significantly impact the Brazil market from 1989 to 2016.

6 Additional Considerations

Several considerations can help in understanding this study. First, the sample size of the data we collected is relatively small, which may not accurately reflect the specific changes in imports when implementing the Time series. Also, to remove as much of the limitation of a small sample as possible, we populated the data set with variables such as Brazilian Gross Domestic Production (GDP), Income, Total Imports, etc., by replicating to match the time scale of Cosmetic Import Value. It is potentially possible to make our time series model more stationary than it actually is. If we are able to obtain more detailed data in the future (ideally weekly data), we will reapply our methods.

Second, we also include China's Gross Domestic Production (GDP) in our model since China is the world's largest cosmetic manufacturer. We believe that its Gross Domestic Production (GDP) may be correlated with cosmetic imports from other countries. Our regression result also shows that China's Gross Domestic Production (GDP) is indeed highly correlated with Brazilian lipstick imports. Due to the globalization of industrial products, it is reasonable to believe that there may be other potential factors that could affect the economic situation and cosmetic imports in Brazil. For example, total Chinese exports to Brazil and the proportion of cosmetics goods, and Gross Domestic Production (GDP) of Brazil's other important trading partners (US, Argentina, Japan), etc.

Furthermore, by analyzing the data on Brazilian lipstick imports over different periods, we find that in some given years (1998, 2014), Brazilian lipstick imports are indeed inversely proportional to Brazil's Gross Domestic Production (GDP). Although these coefficients are not significant, we cannot use these data to confirm the existence of the "lipstick effect" in Brazil. However, they provide us with potentially new insights. We have a reasonable suspicion that a more precise conclusion could be reached if more detailed data were collected for these periods.

We would like to thank the World Bank, IMF, and Quandl for providing free data on the Brazilian economy, making it possible for us to complete this project.

7 Technical Appendix

7.1 Appendix A: Raw Data and Data Set Description

We collected raw data from the IMF, World Bank, and Quandl. These raw data are stored in separate files. It is worth noting that only the value of cosmetic imports (Value) contains month information, so we created two data sets to accommodate two different statistical analysis methods. First, we summed the cosmetic import values for each year to correspond to the year and the remaining variables (see Figure A1). Second, we kept the month information for the import value of cosmetics and repeated the values of the other variables to correspond to Year and Month (see Figure A2).

	Year	Value	BrazilgoodImport	BrazilGDP	ChinaGDP	BrazilIncome	importRatio
1	1989	29921278	1.98850e+10	4.25595e+11	3.47768e+11	2760	0.001504716
2	1990	36672295	2.25220e+10	4.61952e+11	3.60858e+11	2730	0.001628288
3	1991	42389805	2.29470e+10	6.03000e+11	3.83373e+11	3280	0.001847292
4	1992	39019265	2.31160e+10	4.00599e+11	4.26916e+11	3170	0.001687977
5	1993	60161161	2.76040e+10	4.37799e+11	4.44731e+11	3090	0.002179436
6	1994	96292897	3.61920e+10	5.58112e+11	5.64325e+11	3030	0.002660613

(a) A1

	Year	Month	Value	Brazil_GDP	China_GDP	Brazil_income
1	1990	12	701275	3100.280	317.8847	0.1240389
2	1990	11	1590040	3100.280	317.8847	0.1240389
3	1990	10	1104944	3100.280	317.8847	0.1240389
4	1990	9	1856514	3100.280	317.8847	0.1240389
5	1990	8	1231170	3100.280	317.8847	0.1240389
6	1990	7	1414526	3100.280	317.8847	0.1240389
7	1990	6	686387	3100.280	317.8847	0.1240389
8	1990	5	817183	3100.280	317.8847	0.1240389
9	1990	4	631217	3100.280	317.8847	0.1240389

(b) A2

7.2 Appendix B: Additional Tables and Figures used for EDA

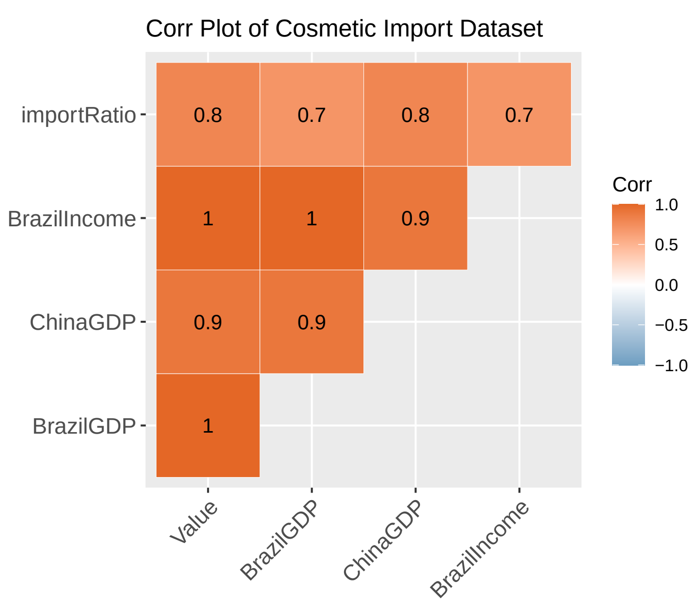

Figure 7: Correlation plots for our data set. We can see that our variables are highly correlated with each other because they are all related to the economic and markets.

7.3 Appendix C: Model Information and Assumption Check

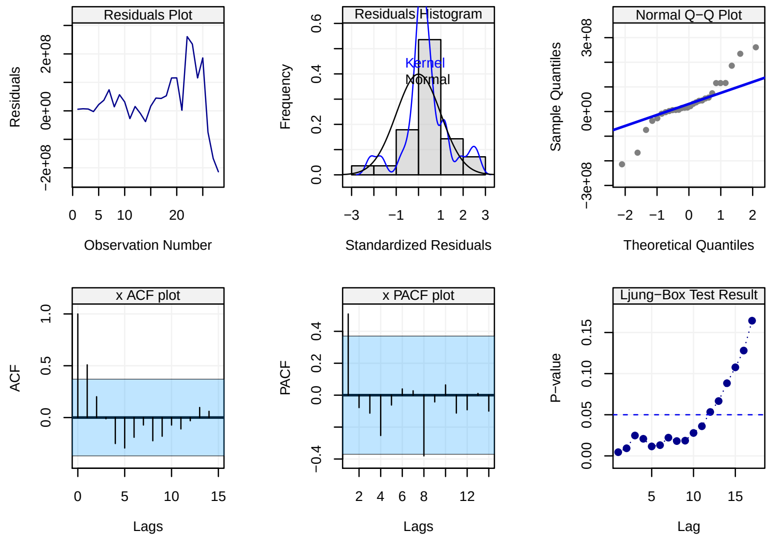

Table C1: Time Series Model check with residuals plot and normal Q-Q plot showing non-stationary and not normality. While the L-jung-Box also shows it is not an ideal model.

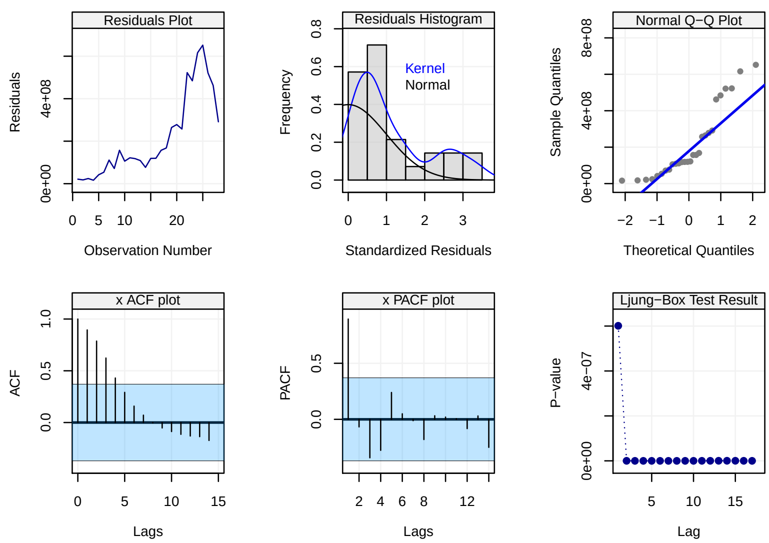

Table C2: MA(1) time series model check, similar results with all residuals plot, unmatched with all assumptions.

Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
511137082	399511713	622762452	340420811	681853353
265107164	41819693	488394634	-76381553	606595881
19077245	-346983822	385138312	-540764845	578919336
-226952673	-759483414	305578068	-1041388160	587482813
-472982592	-1192232677	246267494	-1572980673	627015490

Table C3: Forecasting after eliminating external variables.

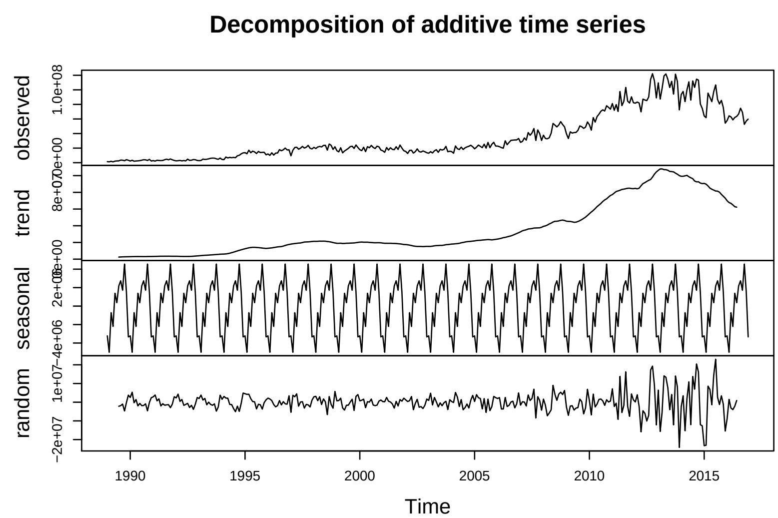

Figure 8: Decompose the time series plot with fours parts. Which is observed (the real time data), the trend (trend after eliminating white noise and seasonal influence), the seasonal (season impact) and the white noise (we can consider it as random walk, factor that would influence model accuracy).

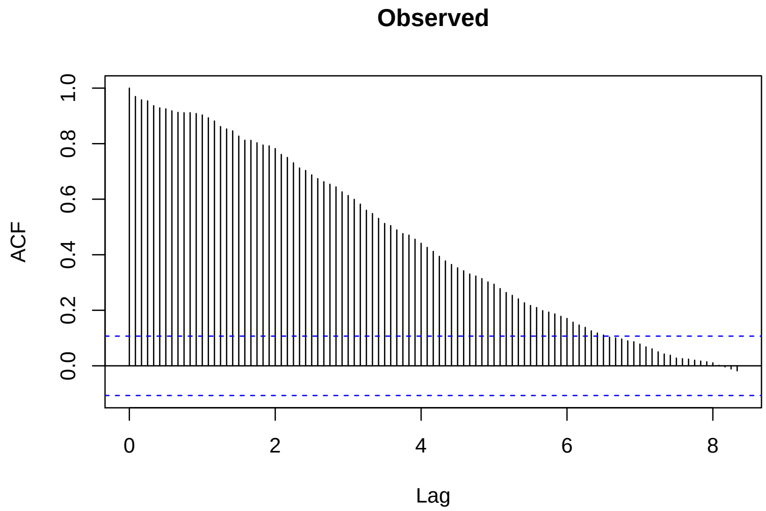

Figure 9: ACF plot showing lags around 6-8 should be carefully considered, as from lags 6-8 would fall into the blue line area indicating the correlation coefficient hypothesis is true.

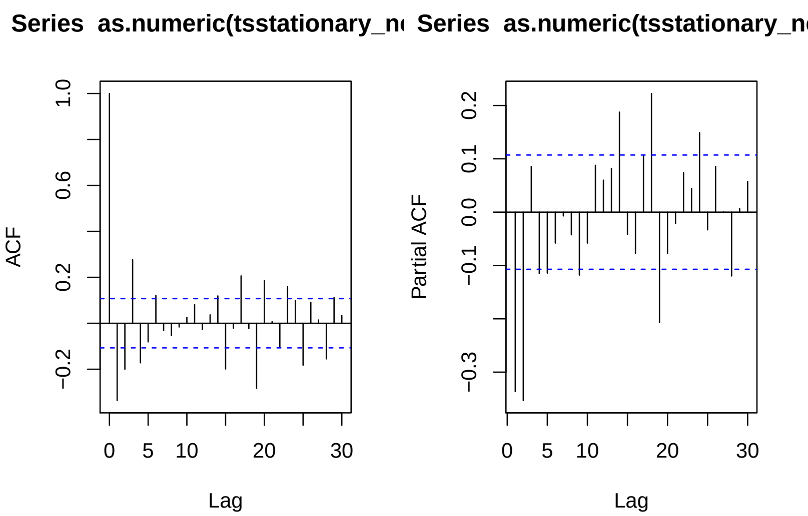

Figure 10: ACF and PACF plots indicating lags from 3-5 should be considered. As from lags 3-5 would fall into blue line area indicating the correlation coefficient hypothesis is true.

```
##
## Call:
## arima(x = tsData, order = c(3, 1, 1))
##
## Coefficients:
##           ar1      ar2     ar3     ma1
##       -0.7601  -0.3890  0.0005  0.3747
## s.e.   0.3221   0.1518  0.1150  0.3173
##
## sigma^2 estimated as 4.655e+13:  log likelihood = -5746.99,  aic = 11503.99
##
## Call:
## arima(x = tsData, order = c(3, 1, 3))
##
## Coefficients:
##           ar1      ar2     ar3      ma1     ma2      ma3
##       -0.0150  -0.6418  0.4389  -0.4149  0.5827  -0.6632
## s.e.   0.1176   0.0750  0.0824   0.1127  0.0842   0.0601
##
## sigma^2 estimated as 4.416e+13:  log likelihood = -5738.44,  aic = 11490.88
```

Table C4: Table showing comparison results of ARIMA(3,1,3) and ARIMA(3,1,1). Focusing on comparing AIC scores, the smaller the better. Meaning we have better fit.

```
##  Best model: ARIMA(3,1,3)(0,0,2)[12]
## Series: tsData
## ARIMA(3,1,3)(0,0,2)[12]
##
## Coefficients:
##           ar1      ar2     ar3      ma1     ma2      ma3    sma1    sma2
##       -0.0473  -0.6403  0.4218  -0.4718  0.5677  -0.6294  0.3032  0.3021
## s.e.   0.1277   0.0869  0.0973   0.1209  0.0718   0.0645  0.0580  0.0583
##
## sigma^2 estimated as 3.902e+13:  log likelihood=-5715.22
## AIC=11448.45   AICc=11449   BIC=11482.78
```

Table C5: Using AIC and BIC scores to show ARIMA(3,1,3) has the least scores which means best fitted.

```
## Formula:
## importRatio ~ ns(BrazilIncome, df = 5) + ns(BrazilGDP, df = 4)
##
## Parametric coefficients:
##                             Estimate Std. Error t value Pr(>|t|)
## (Intercept)                0.0014267  0.0004710   3.029  0.00722 **
## ns(BrazilIncome, df = 5)1  0.0013728  0.0009175   1.496  0.15194
## ns(BrazilIncome, df = 5)2  0.0023122  0.0018456   1.253  0.22631
## ns(BrazilIncome, df = 5)3  0.0059164  0.0027085   2.184  0.04241 *
## ns(BrazilIncome, df = 5)4  0.0074698  0.0028838   2.590  0.01847 *
## ns(BrazilIncome, df = 5)5  0.0070031  0.0025241   2.774  0.01250 *
## ns(BrazilGDP, df = 4)1    -0.0002218  0.0014234  -0.156  0.87792
## ns(BrazilGDP, df = 4)2    -0.0027204  0.0027881  -0.976  0.34213
## ns(BrazilGDP, df = 4)3    -0.0018800  0.0028318  -0.664  0.51517
## ns(BrazilGDP, df = 4)4    -0.0050421  0.0025189  -2.002  0.06062 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
##
## R-sq.(adj) =  0.668   Deviance explained = 77.9%
## GCV = 6.2037e-07  Scale est. = 3.9881e-07  n = 28
```

Table C6: Generalized Additive Model (GAM)'s result shows the Brazilian Gross Domestic Production (GDP) and the Import Ratio of cosmetic goods does have negative relationship but the coefficients are rather small and the correlations are not significant given the large p-values.

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