Why Did Brazil Deindustrialize So Much? Testing The Dutch Disease And Premature Deindustrialization Hypotheses

Edmar L. Bacha* Victor S. Terziani† Claudio M. Considera‡ Eduardo A. Guimarães§

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Abstract

Between 1995 and 2022, Brazil's manufacturing share of GDP at constant prices declined from 15.7% to 9.8% — a 38% drop. This paper tests two leading explanations for this marked deindustrialization: Dutch disease and premature deindustrialization. While both hypotheses find statistical support in our econometric analysis, neither accounts for the actual decline. Exchange rate changes (Dutch disease) would have led to reindustrialization, and the evolution of GDP per capita (premature deindustrialization) would have raised, not reduced, the manufacturing share. A residual time trend explains nearly all of the fall, suggesting that other factors—such as declining industrial competitiveness—are at play.

Resumo

Entre 1995 e 2022, a participação da indústria de transformação no PIB caiu de 15,7% para 9,8% — uma queda de 38%. Este artigo testa duas explicações para essa acentuada desindustrialização: a doença holandesa e a desindustrialização prematura. Embora ambas encontrem respaldo estatístico em nossa análise, nenhuma delas explica a queda observada. Variações do câmbio (doença holandesa) teriam levado à reindustrialização, e a evolução da renda per capita (desindustrialização prematura) deveria ter elevado, e não reduzido, a participação industrial. Uma tendência residual explica quase toda a queda, sugerindo que outros fatores — como a perda de competitividade da indústria — estão em jogo.

Key words: Brazil, Dutch disease, premature deindustrialization

JEL codes: O14, O54, Q02

*Instituto de Estudos de Política Econômica/Casa das Garças. Av. Pe. Leonel Franca 135. 22450-000, Rio de Janeiro, RJ, Brazil. ebacha@iepecdg.com

†Instituto de Estudos de Política Econômica/Casa das Garças. Av. Pe. Leonel Franca 135. 22450-000, Rio de Janeiro, RJ, Brazil. vhsterziani@iepecdg.com.br

‡Instituto Brasileiro de Economia, Fundação Getúlio Vargas. Rua Presidente Carlos de Campos 417. 22231-080, Rio de Janeiro, RJ, Brazil. claudio.considera@fgv.br

§Centro de Estudos para Integração e Desenvolvimento (Cindes). Rua Jardim Botânico 635, suite 906. 22470-050, Rio de Janeiro, RJ, Brazil. eaaguimaraes@gmail.com

1 Introduction[1]

This paper investigates two leading explanations for Brazil's marked deindustrialization from 1995 to 2022. At constant 2005 prices, the manufacturing share of GDP fell from 15.7% in the first quarter of 1995 to 9.8% in the first quarter of 2022—a 5.9 percentage point drop, or 38%.

We focus on two main explanations. The first attributes Brazil's deindustrialization to Dutch disease, triggered by sustained increases in revenues from natural resource sectors. The mechanism involves rising resource revenues appreciating the Brazilian currency, making manufactured exports less competitive and imports cheaper, thereby undermining domestic manufacturing.

The classic model of Dutch disease, proposed by Corden and Neary (1982), notes that cross-border capital inflows seeking to capitalize on a resource boom can reinforce the real exchange rate appreciation. Independent episodes of substantial foreign capital inflows—so-called financial bonanzas—have also been associated with deindustrialization, as discussed by Botta, Yajime, and Porcile (2023).

Bacha (2013) estimates that, between 2005 and 2011, an external windfall—driven by improved terms of trade and large capital inflows—allowed domestic aggregate spending to exceed Brazil's GDP by approximately 9%. He applies a macroeconomic model inspired by Corden and Neary to show that this bonanza could explain Brazil's deindustrialization during the period.

The second hypothesis is premature deindustrialization: a shift of economic activity toward services at income levels where, historically, countries have continued to industrialize. The term "premature"—perhaps first used by Dasgupta and Singh (2007) and Palma (2005)—was canonized in development economics by Rodrik (2016).

Rodrik attributes premature deindustrialization in developing economies to globalization. As countries liberalized trade, those lacking strong comparative advantages in manufacturing became net importers, reversing their previous import substitution trajectories. Moreover, these economies also "imported" deindustrialization from advanced economies via declining relative prices for manufactured goods, a trend that squeezed manufacturing globally.

The emergence of China as a manufacturing powerhouse also helps explain deindus-

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trialization outside Asia. Population aging, according to Cravino, Levchenko, and Rojas (2022), accounted for a fifth of the increase in the service share of consumption between 1982 and 2016 in the U.S. Other factors causing deindustrialization in advanced and developing countries were a trend toward outsourcing activities previously carried out within factories and the rise of high-tech service sectors such as banking and information technology. Morrone, Giovanini, and Berri (2022) claim that part of the manufacturing decline observed in Brazil from 2000 to 2015 is related to activities within the sector that migrated to services. Palma (2005) extends the concept of Dutch disease. He uses it as a case of premature deindustrialization that includes not only natural resource booms, but also the development of export-service activities, mainly tourism and finance, and changes in economic policy (from import substitution industrialization to trade and financial liberalization). In this paper, we stick to the traditional concept of the Dutch disease because its determinants—exchange rate appreciations generated by terms of trade improvements and capital inflows–differ from those that cause premature deindustrialization, as characterized by Rodrik.

Brazil's deindustrialization–understood as a continuous decline in the GDP share of manufacturing at constant prices–probably dates from the late 1970s (cf. Bonelli, Pessoa, and Matos, (2013)), earlier than the initial year of our analysis, 1995. We started in 1995 because a consistent set of quarterly national accounts, as needed for our econometric analysis, dates from this year. In addition, Brazil's official statistics body (IBGE) significantly revised the national accounts in 1995, and figures from previous years are not comparable with those from that date onward.

There are many empirical studies of Brazil's deindustrialization. But to our knowledge, only two papers use econometric models like ours to derive their results. Marconi and Barbi (2011) estimate panel regressions for the period 1995-2007 with the GDP shares of 28 manufacturing sectors in current prices as the dependent variable and the lagged values of the dependent variables, GDP per capita and its square, effective real sectoral exchange rates, GDP shares of gross investment rates, shares of imported inputs in sectoral intermediate consumption, among others, as independent variables. Their results confirm that manufacturing GDP shares are strongly autoregressive and follow an inverted U-shaped path with economic growth but are otherwise inconclusive.

Iasco-Pereira and Morceiro (2024) estimate time series regressions with annual data for the period 1947-2021, with the manufacturing share of GDP in current prices as the dependent variable and the real effective exchange rate and infrastructure investment, among others, as independent variables. They find a significant relationship between the manufacturing share in current prices and the real exchange rate, but this may simply be because relative prices in manufacturing are strongly associated with the real exchange rate. When the real exchange rate appreciates, the relative prices of manufacturing fall, which reduces the current price share of manufacturing in GDP. Thus, a valid test of Dutch disease must use the constant price GDP share of manufacturing as the dependent variable, as Rodrik (2016) points out. Furthermore, an appropriate instrumental variable must replace as a regressor the real exchange rate as this is an endogenous variable. Finally, as shown in Morceiro (2021), using pre-1995 data requires several heroic corrections to make them minimally compatible with the post-1995 national accounts, raising the prospect of measurement errors.

In the next section, we discuss the quarterly evolution of the Brazilian manufacturing share of GDP since 1995 and its possible determinants according to the two hypotheses. We show the evolution of the manufacturing share in current and constant prices. However, in the econometric analysis, we limit our attention to real values, since nominal values conflate movements in quantities and prices, which are best kept separate when trying to understand structural change and its determinants. We do not provide an econometric analysis of the evolution of Brazil's manufacturing employment share, as a consistent series for this variable is available on a quarterly basis only from 2012 onwards.

Section three provides econometric tests of the hypotheses about the causes of Brazil's deindustrialization, considering their aggregate effects and explanatory power. Section four concludes. Appendix A describes the time series econometric tests. Appendix B presents additional regressions. The Data Supplement, available online at iepecdg.com.br, contains all the data we used, including their sources.

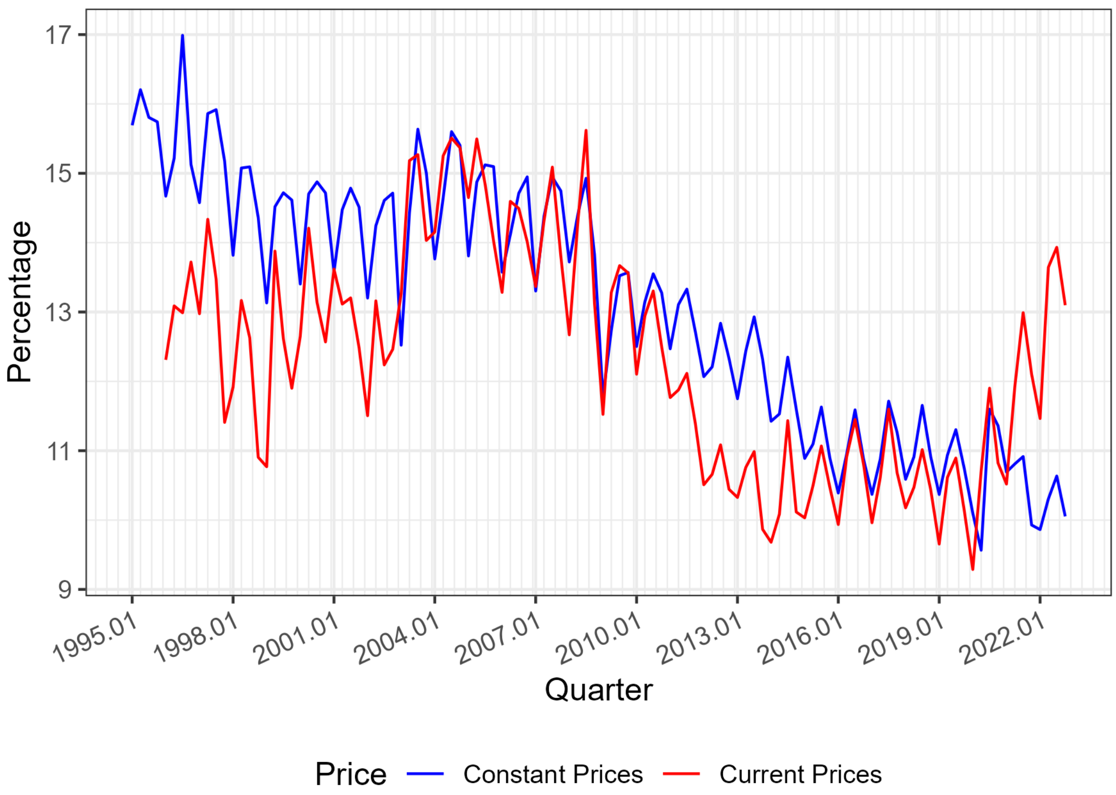
2 Deindustrialization and its interpretations

We use quarterly national accounts data on Brazil's industrialization rates: the share of manufacturing in GDP at constant 2005 prices from 1995.1 to 2022.4 and at current prices from 1996.1 to 2022.4. These are shown in Figure 1 as the blue and orange lines, respectively.

Both series have a pronounced seasonal pattern within the year, with a peak in the third quarter and a trough in the first quarter–more on this in section three. In the following, we make intertemporal comparisons using first quarter data.

Brazil's industrialization rate at current prices starts at 12.3% in 1996.1 and reaches a low of 9.3% in 2020.1, for a total deindustrialization of 3 p.p., or 24%. There is some re-industrialization in current prices in the early years of the period, as the share of manufacturing in GDP rises from 12.3% in 1996.1 to 14.6% in 2005.1. The industrialization rate in current prices changes little from 2005.1 to 2008.1, when it begins a sharp decline

Figure 1: Brazil's Industrialization Rates in Current and Constant Prices, 1995.1-2022.4



Source: IBGE quarterly national accounts, processed by authors.

to 9.7% in 2014.1, a value around which the series stabilizes until 2020.1. After that, the current price series rises sharply and ends at values like those at the beginning of the series. The reindustrialization surges from 1996 to 2005 and from 2020 to 2022 are probably related to the significant depreciations of the Brazilian currency in these periods. Manufacturing products are tradable goods, while most of GDP is non-tradable services. Currency depreciation raises the prices of tradables relative to non-tradables, thereby increasing the share of manufacturing in GDP at current prices.

Thus, at current prices, Brazil's deindustrialization would have occurred only in the six years from 2008 to 2014. Because of the industrial prices surge in 2020-22, measured at the endpoints, there was no deindustrialization at current prices in the whole period.

The picture is different for the GDP share of manufacturing at constant prices, which is the one that matters for our empirical analysis. As the blue line in Figure 1 shows, deindustrialization at constant prices occurs throughout virtually the entire period. In 2005 prices, the GDP share of manufacturing falls from 15.7 percent in 1995.1 to 9.8 percent in 2022.1, a decline of 5.9 percentage points, or 38 percent. Factors behind this sharp deindustrialization are the object of analysis of the following sections.

2.1 The Dutch Disease

According to the Dutch disease hypothesis, Brazil's deindustrialization would result from increased revenues from natural resources and foreign capital inflows. Different indices could describe the strength of natural resource revenues. Still, the terms of trade (i.e., the ratio between the prices of exported and imported goods) are often used in Brazil because the country's exports are largely primary products, while its imports are mainly manufactured goods. We capture the financial component of the Dutch disease with the Dollar Index, which is discussed below.

Figure 2, using data from Funcex [Fundação Centro de Estudos do Comércio Exterior], shows the evolution of Brazil's terms of trade from 1995.1 to 2022.4, with 2005 = 100. [2] The graph illustrates the ups and downs of this variable, with a long upswing from 1999 to 2011 and an upward drift for the whole series. Visually at least, the terms of trade movements roughly coincide with the deindustrialization in constant prices during this period. The graph illustrates the ups and downs of this variable, with a long upswing from 1999 to 2011 and an upward drift for the whole series. Visually at least, the terms of trade movements roughly coincide with the deindustrialization in constant prices during this period.

We analyze the behavior of the real exchange rate with the use of the inflation-adjusted exchange rate of the Real against the U.S. dollar calculated by Brazil's Central Bank.[3] This is because the prices of exports and imports entering the terms of trade are in U.S. dollars; more importantly, many traded goods, especially commodities, are priced in U.S. dollars; moreover, about 90% of Brazil's trade is denominated in this currency.

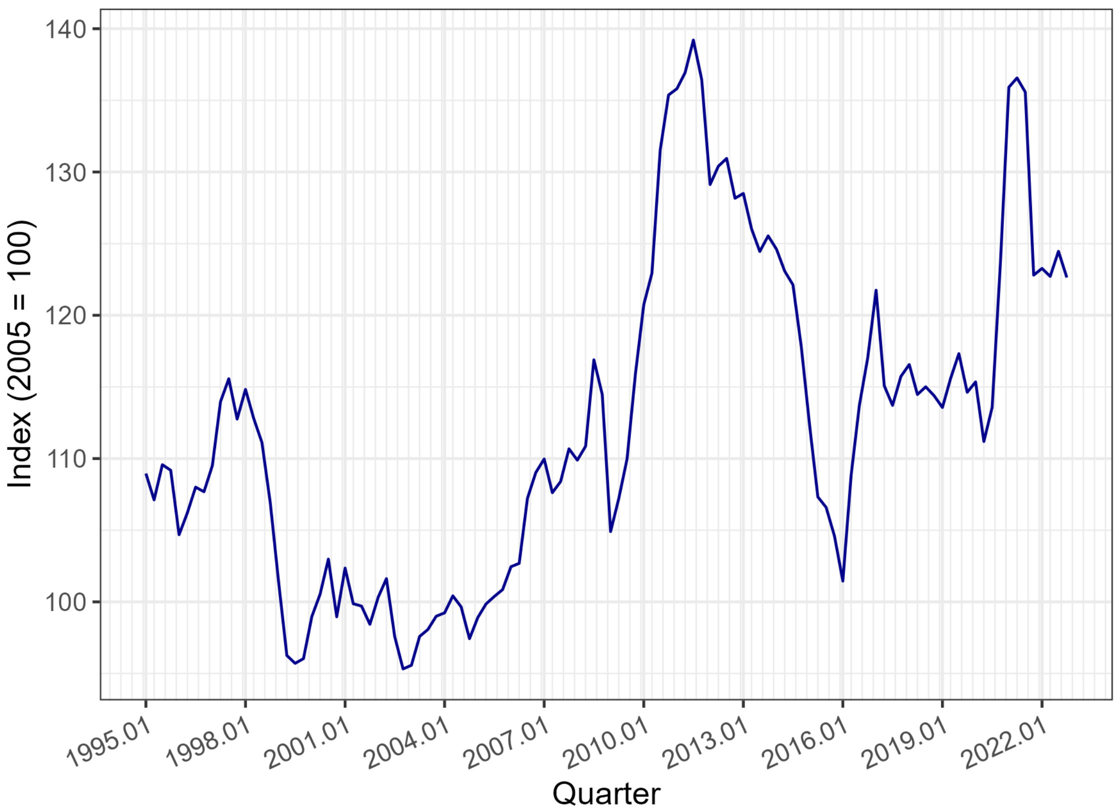
Previous econometric analyses of Brazil's deindustrialization have used the real effective exchange rate (REER) instead of the Real/USD real rate (see Iasco-Pereira and Morceiro (2024) and Marconi and Barbi (2011)). We also performed econometric exercises with the REER and report the results (which are very much like those with the Real/USD real rate) in Appendix B.

Figure 3 shows the volatile behavior of the Real/USD real exchange rate from 1995.1 to 2022.4 (higher values indicate a depreciation of the Real/USD rate). There is relative stability during the managed exchange rate period from 1995.1 to 1998.4. This is followed by a period of sharp depreciation, culminating in 2002.3 with the so-called Fear of Lula effect. Sebastian Edwards' (2002) piece in the Financial Times illustrates the fear of financial market participants that the ascension of the leftist Luiz Inacio Lula da Silva

[2]We thank Henry Pourchet from Funcex for this data.

[3]The price indexes to calculate the inflation-adjusted rates are the IPCA for Brazil and the CPI-U for the U.S. We thank Fernando Rocha and Thiago Vieira, from Brazil's Central Bank, for this data.

Figure 2: Brazil's Terms of Trade, 1995.1 - 2022.4 (2005 = 100)



Source: Funcex, processed by the authors.

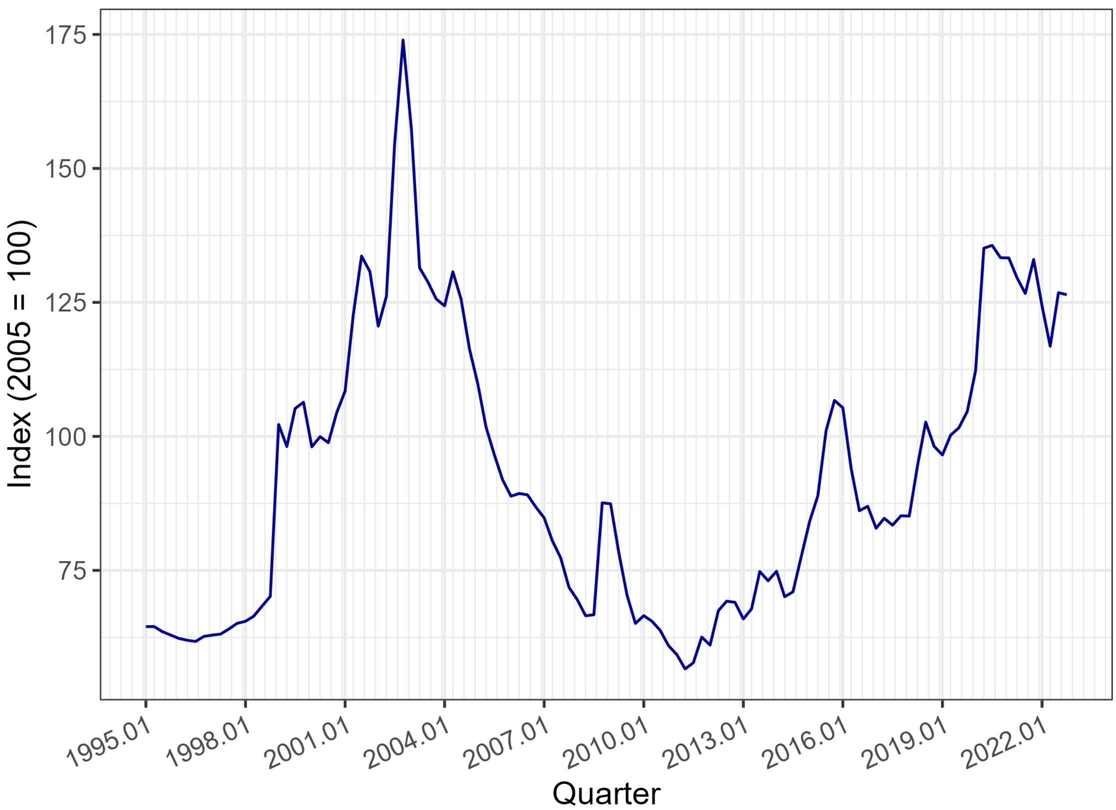
to the presidency of Brazil would lead the country to default on its public debt.

From 2003.1 to 2011.2, Brazil's currency experienced a sharp real appreciation, in line with the China-induced commodity boom. This was followed by a trend of depreciation until the end of the period. We conclude that the terms of trade were an ingredient, but other factors also influenced the behavior of the real exchange rate in the period.

The Dutch disease hypothesis does not postulate a direct relationship between the terms of trade and deindustrialization, as there is an intervening variable, namely the real exchange rate. Supposedly, an improvement in the terms of trade appreciates the real exchange rate, and this appreciation crowds out domestic manufacturing. However, other variables affecting the real exchange rate may influence its impact on industrialization rates.

One particularly important variable is the strength of the U.S. dollar in the global economy, as depicted in Figure 4–this is the U.S. Fed trade-weighted real broad dollar index, the real exchange rate of a basket of currencies against the U.S. dollar, with 2005 = 100 (higher levels indicate U.S. dollar appreciation).

Figure 3: Real/USD Real Exchange Rate, 1995.1-2022.4 (2005 = 100)

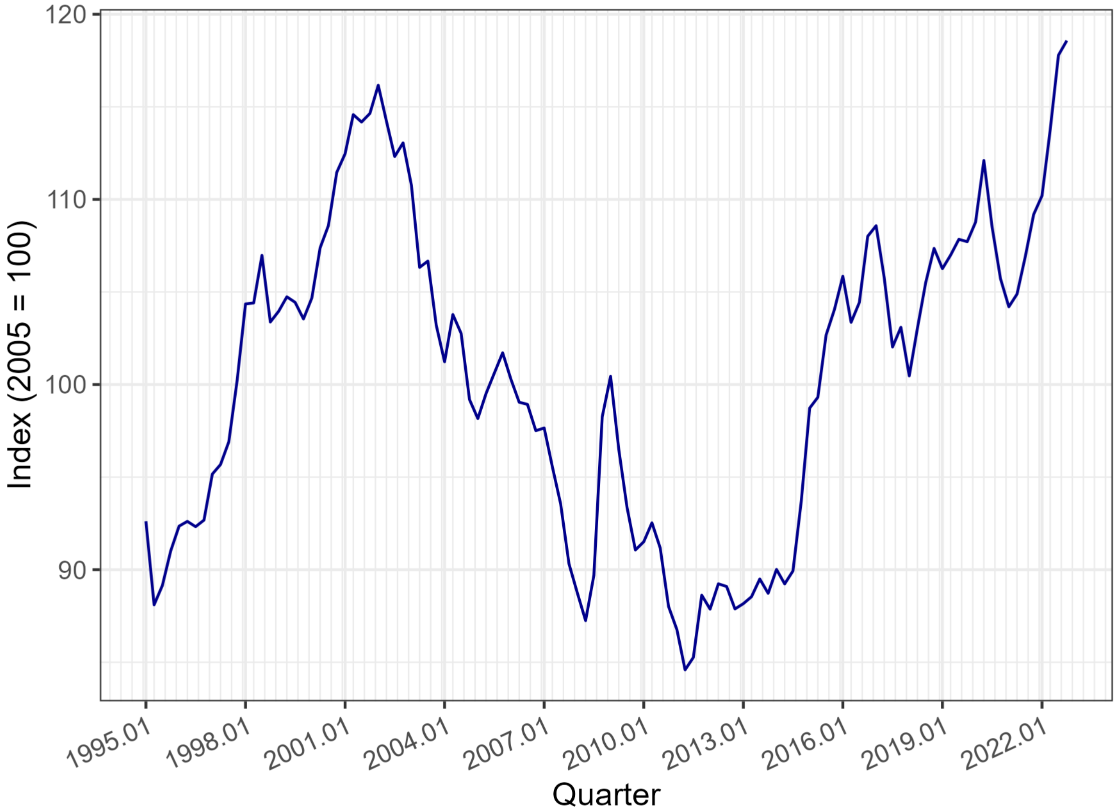


Source: Brazil's Central Bank.

Several recent studies show that movements in the Dollar Index are strongly associated with capital flows to emerging market economies (EMEs) (see Goswami, Pontines, and Mohammed, (2023), for references). Depreciation of the Dollar Index is associated with financial prosperity in EMEs, while appreciation is associated with financial distress in these markets. Thus, the strength of the dollar index is an adequate empirical representation of the financial component of the Dutch disease mentioned, among others, by Botta, Yajime, and Porcile (2023).

The Dollar Index doesn't show a clear trend over the period. However, its cyclical behavior resembles that of the Real/USD rate: it appreciates from 1995 to 2001, depreciates until 2011, and appreciates again until 2022. The econometric analysis in section three confirms the relevance of the Dollar index in the determination of the Real/USD rate.

Figure 4: Real Broad Dollar Index, 1995.1-2022.4 (2005 = 100)



Source: U.S. Fed. The authors merged the old with the new series.

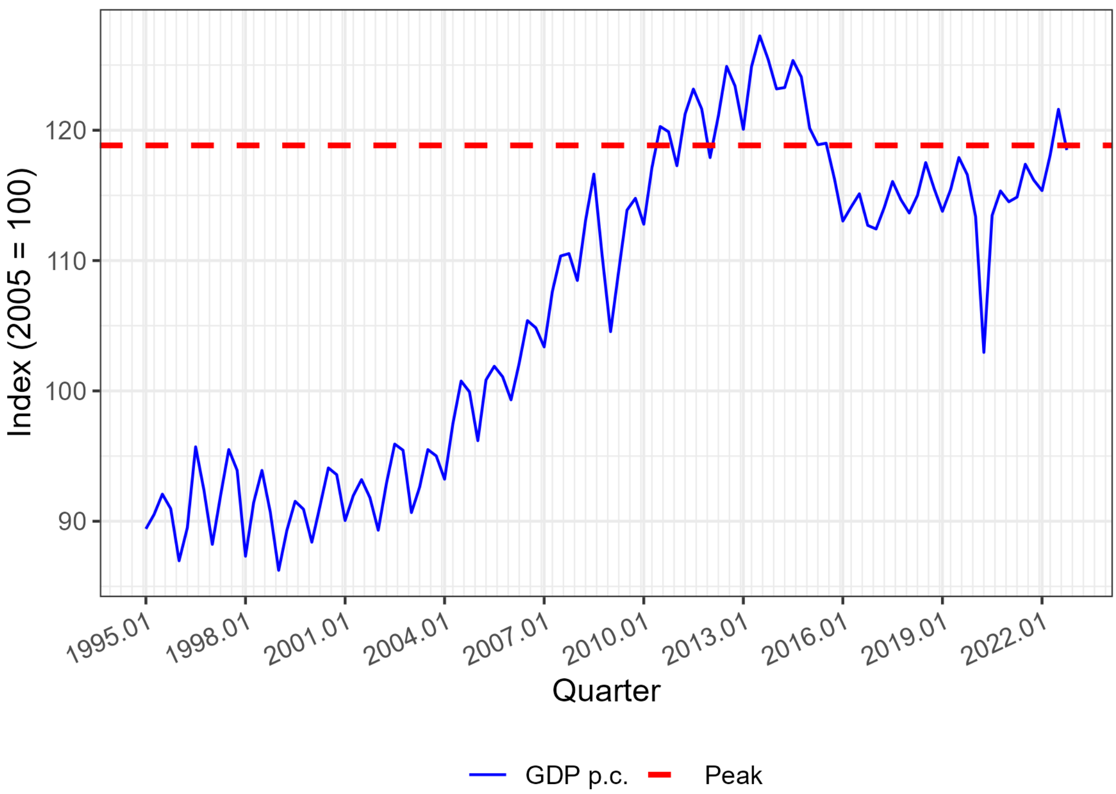
2.2 Premature deindustrialization

To address the hypothesis of premature deindustrialization, as usual in the literature, we specify a quadratic relationship between industrialization rates and Brazil's GDP per capita. Before, we briefly describe the evolution of Brazil's GDP per capita and its apparent relation with the country's industrialization rate.

Figure 5 depicts the evolution of Brazil's GDP per capita (in index number form, with 2005 = 100): slow growth from 1995 to 2002 followed by rapid growth from 2002 to 2014; a sharp contraction to 2016 followed by economic recovery to the end of the period (except for a major drop in 2021 because of the Covid crisis). The dotted red horizontal line is drawn at the income level for which, according to the econometric results in section 3, the industrialization rate reaches a maximum in the period.

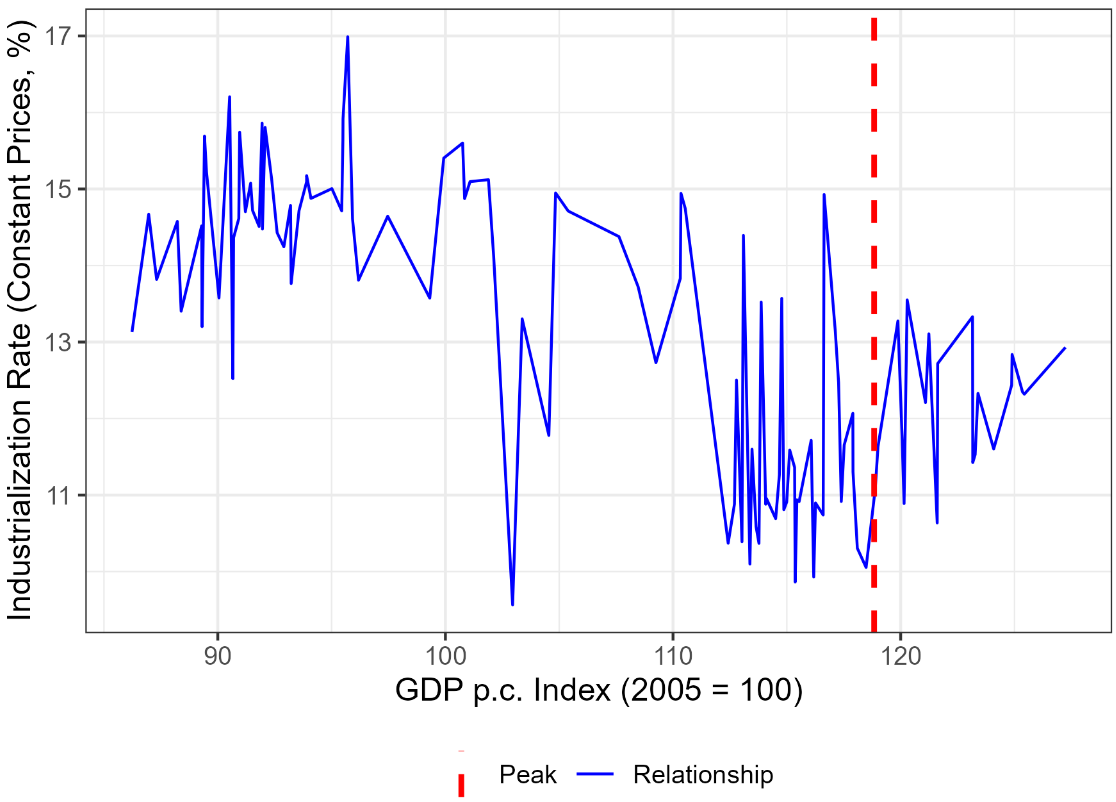
Figure 6 displays the association between the industrialization rate, in the vertical axis, and GDP per capita, in the horizontal axis: ups and downs prevail, but a negative relation is suggested. As in Figure 5, the dotted red vertical line is drawn for the income level at which the industrialization rate reaches a maximum.

Figure 5: Brazil's GDP per capita, 1995.1-2022.4 (2005 = 100)



Sources: IBGE and Ipeadata, processed by authors.

Figure 6: Brazil's industrialization rate (%) as a function of GDP per capita (2005 = 100), 1995.1-2022.4



Sources: IBGE and Ipeadata, processed by authors.

3 Regression Results

We proceed in two steps. First, we estimate a regression of the Real/USD real exchange rate (RER) on Brazil's terms of trade and the broad real dollar index for 1995.1 to 2022.4. We include three dummy variables in this regression: one for 1995.1 to 1998.4, when the exchange rate was managed before the float in January 1999; another for 2002.3 to 2003.1, when the fear of Lula was manifest; and a third for 2020.2 to 2021.4 on account of the Covid crisis.

Next, we use a lagged fitted value of the RER as an independent variable in regressions for the GDP share of manufacturing in Brazil at constant prices (which we also refer to as Brazil's industrialization rate), in the 1996.1-2022.4 period. This variable captures the Dutch disease effect. Preliminary tests with eight different lags indicated which performed better. Results of using the real effective exchange rate instead of the Real/USD real rate are presented in Appendix B.

To capture the premature deindustrialization effect, we include both GDP per capita (GDPpc) and its square (GDPpc^2) as regressors. To generate the anticipated inverse-U relationship between industrialization and income, the coefficient of GDPpc should be positive and that of GDPpc^2 negative.

Another regressor is a time trend. This is designed to capture the effect of variables other than those used to estimate the Dutch disease and the premature deindustrialization hypotheses. We also display the results of a regression without the time trend to show that it is indeed needed for a satisfactory explanation of the behavior of the industrialization rate in the period.

Two lagged values of the dependent variable are also included in the regressions (we experimented with other lag structures, but results were better with the two immediately preceding lags). This is justified both economically—since the industrialization rate is a slow-moving variable—and statistically, as the lags help alleviate bias generated by autocorrelation in the residuals.

Finally, we include seasonal (quarterly) dummies to capture intra-annual variation in the industrialization rate.

In Appendix A, we present a series of statistical tests to evaluate the validity of our regressions. The residual autocorrelation and partial autocorrelation functions demonstrate the absence of individual residual autocorrelation in our regressions. Along with the results of the Ljung-Box tests, we conclude that there should not be any residual autocorrelation in the regressions, implying that the estimators are consistent. Since the real exchange rate regression does not include lags of the dependent variable as a regressor, residual autocorrelation should not affect the consistency of the estimators in this case.

Appendix A also presents the results of the Engle-Granger cointegration test for both first and second stage regressions. The Engle-Granger test performs a unit-root test–we use the Augmented Dickey-Fuller (ADF) test–in the regression residuals. They indicate that none of the regressions exhibit integrated residuals, even though all dependent variables are integrated. This provides evidence that the variables are cointegrated and the regressions are not spurious but indicate genuine relationships.

The results of the regressions are summarized in Table 1. The coefficients are all linear, and in the case of the industrialization rate, they indicate short-term effects. We comment on the elasticities derived from the linear coefficients of the RER regression. These are calculated at the mean values of the relevant variables. For the industrialization rate regressions, we comment on short- and long-run effects. The former are expressed directly by the linear coefficients, the latter by these coefficients multiplied by $\frac{1}{(1-z)}$, where z is the sum of the coefficients of the two lagged values of the dependent variable. For example, the value of z in the regression in column (2) of Table 1 is 0.441 (= 0.216+0.225), which yields $\frac{1}{(1-z)} = 1.79$.

Table 2 summarizes the dependent variables' responses to changes in the independent variables calculated from regressions (1) and (2) in Table 1.

First, consider the regression for the real exchange rate (RER) in column (1) of Table 1. As expected, this variable is highly dependent on Brazil's terms of trade, with a coefficient of -0.55 and an elasticity of -0.67 (the mean of RER is 92.46, and the mean of the terms of trade is 112.48). As summarized in Table 2, when the terms of trade rise by 1%, the real exchange rate appreciates by 0.67%. The Real/USD exchange rate is even more dependent on the dollar index, with a coefficient of 1.6 and an elasticity of 1.74 (the mean of the dollar index is 100.38). A 1% rise in the dollar index leads to a 1.74% depreciation of the Real to the U.S. dollar. This shows that the USD value of Brazil's currency is highly sensitive to the dollar's strength in the world economy.

The coefficients of the dummy variables have the expected sign: a 22 p.p. (or 24%) appreciation during the managed exchange rate period from 1995.1 to 1998.4; a 42 p.p. (or 45%) depreciation with the fear of Lula from 2002.3 to 2003.1; and a 36 p.p. (or 39%) depreciation with the Covid crisis from 2020.2 to 2021.4. The percentage changes are calculated at the mean of the RER, which is 92.46. Such sharp fluctuations reveal the sensitivity of Brazil's currency to domestic and external shocks.

We now turn to the two regressions in Table 1 regarding Brazil's industrialization rate. The only difference between these regressions is that column (2) includes the time trend

Table 1: Regression results

	RER	Industrialization Rate - Constant Prices	
	(1)	(2)	(3)
Constant	-6.3302	-19.4250***	-4.7383
	(0.7612)	(0.0000)	(0.3080)
Terms of Trade	-0.5520***		
	(0.0000)		
Real Broad Dollar Index	1.6010***		
	(0.0000)		
Dummy Managed	-22.5163***		
	(0.0000)		
Dummy Lula	42.0404***		
	(0.0000)		
Dummy Covid	36.1722***		
	(0.0000)		
1st Lag - Industrialization Rate		0.2157+	0.5454***
		(0.0643)	(0.0000)
2nd Lag - Industrialization Rate		0.2254*	0.4338***
		(0.0461)	(0.0007)
3rd Lag - Fitted RER		0.0092***	0.0018
		(0.0001)	(0.5377)
GDP p.c.		0.4782***	0.0721
		(0.0000)	(0.4411)
GDP p.c. squared		-0.0020***	-0.0004
		(0.0000)	(0.4340)
Time Trend		-0.0485***	
		(0.0000)	
2nd Quarter		0.9236***	1.4720***
		(0.0000)	(0.0000)
3rd Quarter		1.4887***	2.1244***
		(0.0000)	(0.0000)
4th Quarter		0.8125***	0.9941***
		(0.0000)	(0.0000)
Observations	112	109	109
R^2	0.882	0.965	0.946
Adjusted R^2	0.876	0.962	0.941
RMSE	9.08	1.17	1.17

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001
P-Values between parentheses.

while column (3) does not. Without the time trend, the coefficients of RER, GDPpc, and GDPpc^2 are not significant. With the time trend, these coefficients become highly significant. For this reason, we'll ignore column (3) and analyze only the coefficients in the regression in column (2). We consider initially the auxiliary variables, by which we mean the lagged dependent variables and the seasonal dummies.

We already commented that the coefficients of the dependent variable lagged one and two quarters sum to 0.441 (other lag structures were tested, but this proved to be the more significant). This means that 44.1% of the total effect of the other independent variables on the industrialization rate takes effect after the current quarter. That is, to

Table 2: Responses of dependent variables to changes in independent variables calculated from regressions (1) and (2) in Table 1

Percent change* of the real Real/USD exchange rate in response to:		
1% increase in terms of trade		-0.67
1% appreciation of the real dollar index		1.74
Managed exchange rate regime		-23.8
Fear of Lula		45.4
Covid		38.9
Percentage point change of Brazil's industrialization rate in response to:		
	Short-run	Long-run
10 pp depreciation in RER	0.09	0.16
10 pp rise in GDP p.c.**	0.47	0.85
Plus 1 year (time trend)	-0.194	-0.35

*Calculated at the means of the variables. A positive value indicates depreciation.
**Calculated at the average GDP p.c. for 2022, which is 118.39% of 2005 GDP p.c.

obtain the total or long-term effect of an independent variable on the industrialization rate we must multiply its coefficient by $\frac{1}{(1-0.441)} = 1.79$.

According to the seasonal dummies, compared to the 1st quarter the industrialization rate is 0.9 pp higher in the 2^{nd} quarter, 1.5 pp higher in the 3^{rd} , and 0.8 pp higher in the 4^{th}. Seasonal variations within the year are pronounced. In addition to the negative effect on industrial production of the collective holidays in the Southern Hemisphere summer months of January and February, the trough in the 1st quarter may also be because 1/3 of agricultural production is accounted for in this quarter. The peak in the 3^{rd} quarter is probably explained by an acceleration of industrial production in anticipation of higher sales at the end of the year.

We now shift attention to the main regressors, standing for Dutch disease, premature industrialization, and residual trend.

3.1 Aggregate Effects and Explanatory Power of the Main Regressors

The variables standing for the Dutch disease and the premature deindustrialization hypotheses are statistically significant in the regression.

Consider first the Dutch disease with its effect measured by the coefficient of the third lag of the RER in the regression in column (2), which is 0.0092. At the RER mean, a 10% appreciation of the RER reduces the industrialization rate by .092 pp on impact. This effect needs to be multiplied by 1.79 to obtain -0.16 as the long-run effect of the RER on the industrialization rate. In the long run, a 10% appreciation of the RER reduces the industrialization rate by 0.16 pp.

The marginal effect is as expected, but the difficulty with the Dutch Disease hypothesis to explain the deindustrialization is that, as Figure 3 shows, only in eight years of the 27 years in the sample, from 2003 to 2011, did the RER appreciate. In the previous eight years, from 1995 to 2003, it depreciated, with the same happening in the eleven years from 2011 to 2022. In 2022, the RER was 93.5% higher than in 1995, reflecting a substantial real depreciation. If the RER were the sole determinant, Brazil's level of industrialization in 2022 would have exceeded that of 1995.

We also tested the hypothesis that Brazil's manufacturing share would react more strongly to appreciations than to depreciations of the RER. Presumably because in the first case use of preexisting industrial capacity would be reduced, whereas in the second case capacity expansion would be required. This hypothesis was tested with the inclusion of three multiplicative dummies on the RER, respectively for 1995-2002 (first depreciation cycle), 2003-2011 (single appreciation cycle), and 2012-2022 (second depreciation cycle). Only the coefficient for the first of these cycles proved significant, and the coefficient for the appreciation cycle was the smallest. Reaction asymmetries to explain the Dutch disease are not validated in our data.

The signs and statistical significance of the coefficients of GDPpc and GDPpc^2 confirm the existence of an inverted-U relationship between the industrialization rate and per capita income. From these coefficients, we estimate that the level of GDPpc that maximizes the industrialization rate, expressed in 1990 international dollars, is equal to USD 6,955. This value is significantly lower than the USD 22,537 that Rodrik ((2016), Table 10, p. 23) estimates as the turning point of the industrialization rate for his sample of 40 countries in the post-1990 period. [4]

Our results confirm the premature deindustrialization hypothesis in the sense that Brazil started deindustrializing at a much lower GDPpc than the world average, as estimated by Rodrik (2016). Two qualifications needed to be noted. First, Rodrik's panel-based equations are different from ours, which are derived from a time series for Brazil alone including the RER and a time trend, which is not the case with Rodrik's—results from the two exercises may not be fully comparable. Second, as we mentioned in the introduction, Brazil's deindustrialization—understood as a continuous decline of the in-

[4] We take the derivative of the industrialization rate with respect to GDPpc, which is approximately equal to $0.478 + 2 \times (-0.002) \times \text{GDPpc}$. Equating this to zero we calculate the level of GDPpc that maximizes the industrialization rate as 118.82 (this is an index number with 2005 = 100). Then, we convert the index number to 1990 international dollars using the data for Brazil from Bolt and van Zanden (2014). For more details, see the online Data Supplement.

dustrialization rate—probably dates from the mid-1970s. Unfortunately, both because of the unavailability of quarterly data and substantial methodological changes in the national accounts since 1995, we cannot extend our sample period back to the 1970s. If we could, it might be that the turning point that we identify in 2010 would have to be moved back in time — but this would only mean that it occurred at an even lower per capita income than we identify.

The main issue with characterizing Brazil's deindustrialization in the period as generated by the evolution of GDPpc, as postulated by the premature industrialization hypothesis, is that the regression results suggest otherwise. According to the estimates, industrialization increases with GDPpc with a coefficient of 0.478, and declines with GDPpc^2 at a much smaller rate, with a coefficient of just 0.0020. When we compute the combined effect of these two variables over the entire period, their net effect is positive. Based solely on changes in GDPpc, Brazil's industrialization rate would have been higher in 2022 than it was in 1995.

Indeed, the time trend emerges as the only variable that effectively explains Brazil's deindustrialization: according to its coefficient in the regression in column (2), the industrialization rate falls by 0.0485 pp each quarter, or 0.194 pp per year. For the 27 years between the 4th quarters of 1995 and 2022, the time trend alone would imply a reduction of 5.24 percentage points ($= 0.194 \times 27$) in Brazil's industrialization rate. This accounts for 92% of the total 5.69 percentage point decline observed over the period. If we allow for long-run effects, by itself the time trend would generate a deindustrialization of 9.4 pp ($= 5.24 \times 1.79$), which exceeds the actual decline by more than 60%.

Figure 7 provides another perspective on the relevance of each independent variable: their contributions to the coefficient of determination (R^2) of the regression in column (2) of Table 1.

It employs the Shapley Value decomposition method proposed by Lipovetsky and Conklin (2001) to evaluate the relative importance of each regressor in explaining the model's total variance.[5]

The upper part of the figure depicts the relative contributions of all independent variables (full predictors' pool) and the lower part restricts the analysis to the contributions of the time trend, RER, GDPpc and GDPpc square (restricted predictors' pool). This

[5]This approach is drawn from cooperative game theory and attributes the overall R^2 contribution to each independent variable based on its marginal contribution across all possible permutations of the regressors. In practical terms, it calculates how much the regressor improves the model's explanatory power when added to a given subset of regressors. By averaging the marginal gain across all possible subsets, the method yields a fair and robust measure of each variable's importance, even in the presence of multicollinearity or interaction effects. For additional details, see Lipovetsky and Conklin (2001) and Grömping (2007).

lower part pictures the time trend as the most relevant variable, and the RER as the least important. GDPpc and GDPpc square are also relevant, but they operate in opposite directions in the determination of the industrialization rate.

4 Conclusions

Using data from 1995 to 2022, we investigate two current hypotheses about Brazil's deindustrialization, Dutch disease and premature deindustrialization. We capture Dutch disease through real exchange rate appreciation (as generated by terms of trade improvement and capital inflows), premature deindustrialization by the evolution of Brazil's GDP per capita. We also include a time trend in the regressions, to capture the effect of variables other than those embedded in the Dutch disease and the premature industrialization hypotheses.

It turns out that the time trend is the only relevant factor explaining deindustrialization over the period. In fact, it more than accounts for the observed deindustrialization. It the short-run, it accounts for 92% of it, and in the long-run for 165%.

Our results confirmed that RER appreciations lead to deindustrialization. But, in the observation period, the RER depreciated significantly (except for an interval between 2003 and 2011): by itself the RER would have generated more industrialization not less. While Dutch disease is detectable in the data, its overall impact appears limited.

We also confirmed the significance of the premature industrialization hypothesis, in the sense that Brazil deindustrialized at much lower income levels than the rest of the world. However, in our regression, the reindustrialization generated in the upward sloping segment of the inverted-U relationship between industrialization and income was higher than the deindustrialization in its downward sloping segment. All together the income movements by themselves would have generated more, not less, industrialization in the 1995 to 2022 period. Premature deindustrialization is evident, yet it cannot fully explain Brazil's trajectory over the period.

Our results suggest searching for hypotheses other than Dutch disease and premature deindustrialization to explain Brazil's deindustrialization. We suspect that the negative evolution of Brazil's industrial competitiveness vis-à-vis other domestic economic activities, especially the agribusiness complex, might explain Brazil's deindustrialization. Data collected in Veloso et al. (2024) indicates that labor productivity in manufacturing declined relative to that of the overall economy. The analysis of the consequences of this trend for Brazil's deindustrialization will be the object of a forthcoming paper.

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Appendix A - Statistical Tests

In this appendix, we provide a series of statistical tests to assess the validity of our regressions. Figures A1 and A2 present the Autocorrelation Functions (ACF) and Partial Autocorrelation Functions (PACF) of our autoregressive estimation [regression (2) of Table 1] examining individual residual autocorrelation in each of the first 20 lags. Table A1 presents the Ljung-Box test results with 10 lags to assess joint residual autocorrelation of regression (2). Table A2 includes the Engle-Granger test to determine whether the regression residuals have a unit root, indicating cointegration in all regressions.

Figure A1: Autocorrelation Function – Regression (2) Residuals

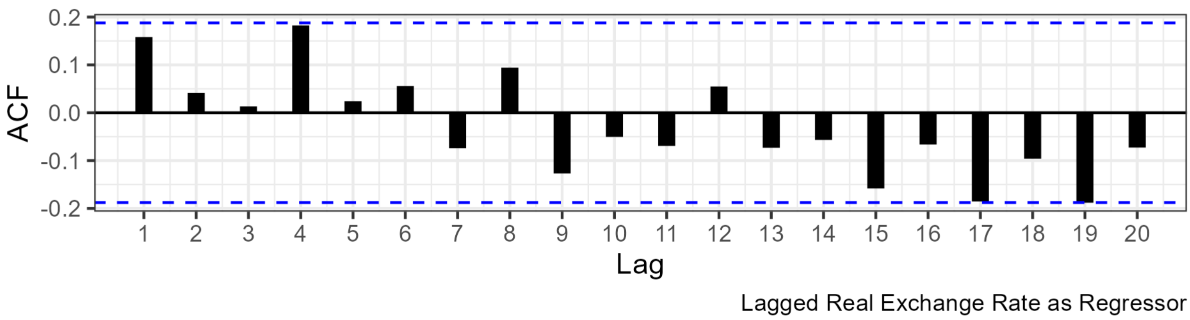
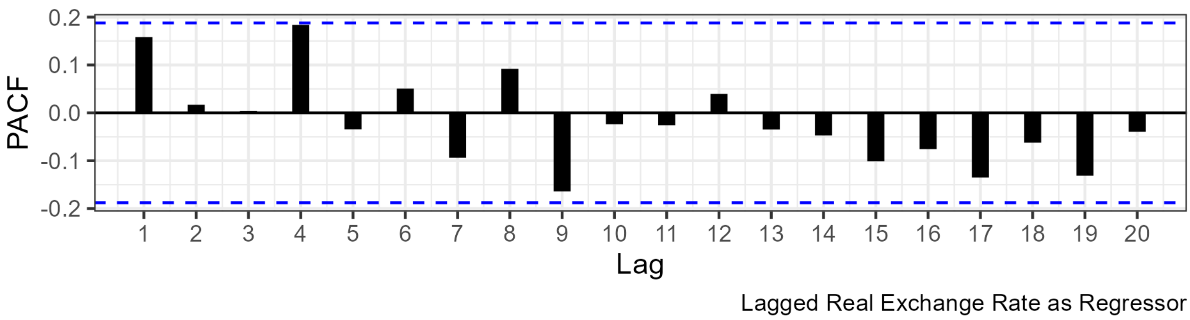


Figure A2: Partial Autocorrelation Function - Regression (2) Residuals



The figures clearly show that no lag exceeds the confidence interval bounds of the zero value in the ACF or PACF. Therefore, individual autocorrelation must not be present in the first 20 lags.

Table A1: Ljung-Box tests

	Industrialization Rate (2)
Test Statistic	11.257
	(0.188)

P-values under coefficients.

Table A1 presents results of a Ljung-Box test for regression (2) of Table 1. The p-value for the Ljung-Box test is greater than 5%, so we can't reject the null hypothesis of no joint residual autocorrelation for 10 lags.

Table A2: Engle-Granger tests

	RER (1)	Ind. Rate (RER) (2)
Test Statistic	-3.085	-6.614
	(0.003)	(<0.001)
Critical Value at 1%	-2.58	-2.58
Critical Value at 5%	-1.95	-1.95
Observations	112	109

P-values under coefficients.

The first column of Table A2 presents results for regression (1), the first stage regression of the real exchange rate. The second column presents results for regression (2), which uses the real exchange rate as a regressor. All test statistics are smaller than their critical values at the 1% significance level. Therefore, we reject the null hypotheses of integrated residuals and, since both the RER and the Industrialization Rate are clearly non-stationary, we conclude that the variables have a non-integrated linear combination, indicating that they are cointegrated.

Appendix B - Alternative Specifications

In Table B1, the first column shows the first stage regression of an Instrumental Variable (IV) estimation where the real effective exchange rate (REER) is the dependent variable[6]. The coefficients for the terms of trade, the real broad dollar index, and the exogenous shocks aren't very different from those in the RER regression. The R-squared of the first stage regression is also close to that in column (1) of Table 1, indicating that the instruments are similarly strong when applied to the REER.

[6]This is the index of the real effective exchange rate of Brazil's Central Bank.

The second column shows the second-stage regression of the IV estimation, where the 3^{rd} lag of the fitted REER is the independent variable. The coefficient for the REER (=0.011) is only marginally higher than the coefficient for the RER (=0.009) in Table 1. The coefficients of the other second-stage regressors are also near those in Table 1.

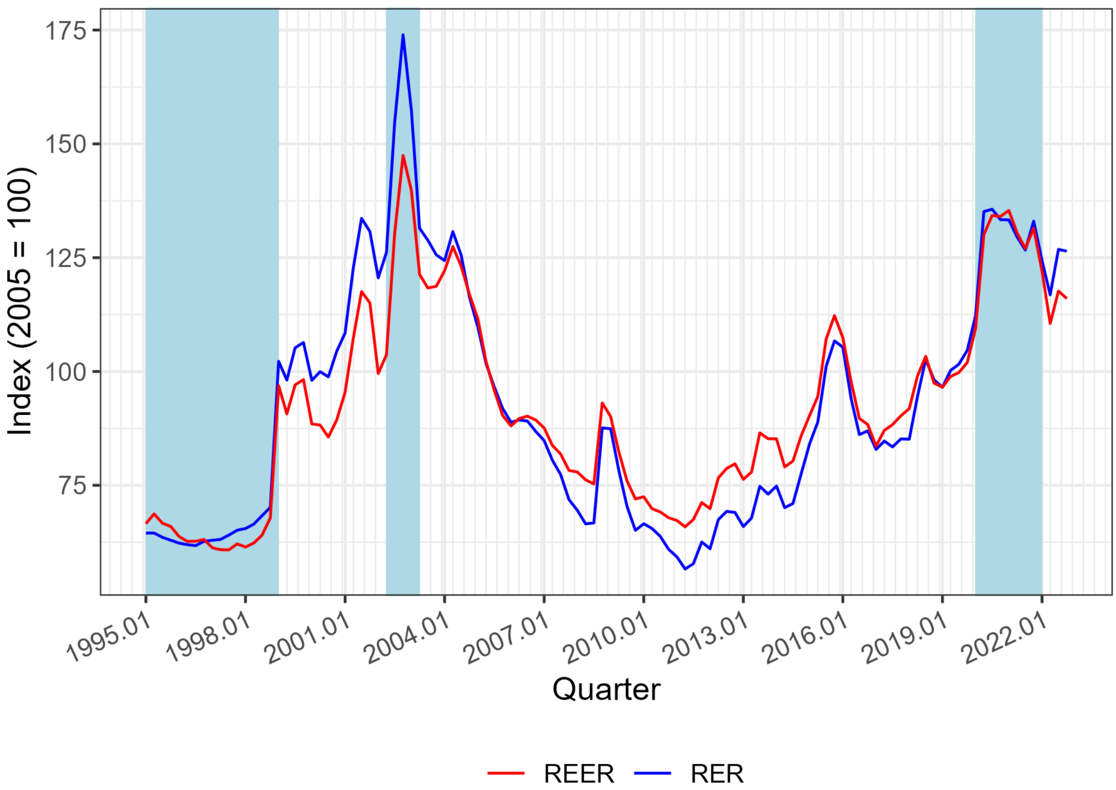
Figure B1 presents the parallel evolutions of the RER and the REER. The exogenous shock periods of the Managed Exchange Rate, the Fear of Lula, and the COVID-19 pandemic are identified in light blue. These external shocks similarly affected the REER and RER.

Table B1: REER Regression Results

	REER	BR Ind. Rate - Con.
	(1)	(2)
Constant	41.454*	-18.402***
	(0.049)	(<0.001)
Terms of Trade	-0.387***	
	(<0.001)	
Real Broad Dollar Index	0.946***	
	(<0.001)	
Dummy Managed	-25.958***	
	(<0.001)	
Dummy Lula	29.038***	
	(<0.001)	
Dummy Covid	37.513***	
	(<0.001)	
1st Lag - Industrialization Rate		0.212+
		(0.080)
2nd Lag - Industrialization Rate		0.210+
		(0.071)
3rd Lag - Fitted REER		0.011***
		(<0.001)
GDP p.c.		0.465***
		(<0.001)
GDP p.c. squared		-0.002***
		(<0.001)
Time Trend		-0.050***
		(<0.001)
2nd Quarter		0.919***
		(<0.001)
3rd Quarter		1.478***
		(<0.001)
4th Quarter		0.813***
		(<0.001)
Observations	112	109
R^2	0.820	0.964
Adjusted R^2	0.812	0.960
RMSE	9.10	1.17

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
P-Values between parentheses.

Figure B1: Real/USD Real Exchange Rate and Real Effective Exchange Rate, 1995.1-2022.4 (2005 = 100)



Source: Brazil's Central Bank. Blue rectangles cover the shock periods.