The Brazilian Real Exchange Rate during the Covid-19 Pandemic[*]

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Abstract

The Covid-19 pandemic period was unprecedented. In this paper, we analyze the behavior of the Brazilian real exchange rate during that period. To this end, we estimate an equilibrium path of the real exchange rate using an Error Correction Model. First, we verify whether movements on the exchange rate can be explained by fundamentals or they constitute a misalignment. According to our results, the real exchange rate was in line with its determinants during the pandemic, despite its strong depreciation. Second, we find the Balassa-Samuelson effect was the main driver of the exchange rate depreciation. However, the impact of the terms of trade was in the opposite direction of the Balassa-Samuelson effect, which prevented a greater exchange rate depreciation.

Keywords: Balassa-Samuelson effect, equilibrium exchange rate, Covid-19 pandemic.
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The views expressed in this paper are those of the authors and do not necessarily reflect those of the Banco Central do Brasil.

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1 Introduction

During the Covid-19 pandemic the Brazilian nominal exchange rate rose sharply, jumping from just over R$ 4/US$ to almost R$ 6/US$. At the same time, the real exchange rate hiked around 30%. This unusual movement raises some important questions. Is it due to changes on economic fundamentals? Or, is it just a noise generated by myopic traders? Is there a misalignment regarding the equilibrium value? What explains this currency movement? What are the main drivers of that abrupt depreciation of Brazilian Real? In this work, we shed some lights on these questions through the lens of a real exchange rate equilibrium model.

Although we study a long time span - from 2002 to 2022, we focus our analysis in the Covid-19 pandemic period. This period was marked by a global deep recession. The lock-down measures affected the supply of and demand for products, goods and services. People around the world changed their leisure and working habits. As a result, intense prices fluctuations occurred within this period. These prices changes impacted the Balassa-Samuelson effect, assessed through the relationship between tradable and non-tradable prices, as well as the terms of trade, characterized as the ratio between the prices of exports and imports.[1] We observe these two factors moved in opposite directions in the pandemic period: while the Balassa-Samuelson effect increased, the terms of trade decreased. Moreover, the recovery from the crisis was uneven. A possible emergence of a novel business organization raised the question of how permanent the effects of the Covid-19 crisis would be. All in all, this new environment motivated us to investigate the behavior of the exchange rate and identify possible structural changes during the pandemic period.

Equilibrium models allow us to test the consistency of real exchange rates with economic fundamentals. There are a myriad of such models. For details of these models we refer the reader to the nice survey of MacDonald (2000). In this work, we adopt the Behavioral Equilibrium Exchange Rate (BEER) model as our framework to address our questions of interest. The BEER model uses econometric methods to obtain a long-run behavioral link between the exchange rate and relevant economic variables. Nowadays, BEER is the workhorse of the equilibrium exchange rate modeling.

More specifically, we use the same methodology of Hambur et al. (2015), which employs a BEER model to study the Australian dollar exchange rate. Brazil and Australia share exports features. Both countries are exporters of commodities such as iron ore.[2] They also have similar trading partners. Moreover, Brazil and Australia adopt floating

[1] Béla Balassa and Paul Samuelson independently proposed this effect in the early 1960s (see Balassa, 1964, and Samuelson, 1964).

[2] The relation between currencies of commodity exporters countries and commodities prices is robust both in-sample and out-sample (see Chen, Rogoff and Rossi, 2010).

exchange rate regime. Hambur et al. (2015) implement the BEER model in two stages through an Error Correction Model (ECM). The first stage is a cointegrating relation that writes the real exchange rate as a function of its long-run determinants. By assuming equilibrium in the current account, it is possible to obtain this relation theoretically, as shown in MacDonald (2000). We follow this approach, what gives to our study a flavor of the Fundamental Equilibrium Exchange Rate (FEER) models, without the giant difficulties of making assumptions on the long-run values of the economic fundamentals. In the second stage, we estimate a relation that, besides the error correction factor, includes some variables to account for short-run variations of the real exchange rate.

An important issue regarding our study is the choice of the economic and finance variables that work as determinants of the exchange rate. In this point, we follow the mainstream of the literature. For the long-run dynamics, we consider the terms of trade, the interest rate differential, and the Balassa-Samuelson effect, which represents differences in the relative productivity of the tradable and non-tradable sectors. In order to better explain the short-run movements, we also included information from commodity and stock market indexes and variables to capture risk sentiment. Several variables present different proxies that depend on the methodology used to build them. We test alternatives proxies in the same model. As result, we have one model with many specifications, each one of them characterized by a different set of proxies. Our results use all specifications. We believe this approach increases the robustness of the results.

In a nutshell, our results can be summarized as follow. First, we compare equilibrium exchange rate path generated by BEER model to the observed exchange rate trajectory. This exercise presents evidence of some misalignment in past crisis, such as the subprime crisis. However, during the Covid-19 crisis, despite the strong depreciation of the Brazilian exchange rate, its path was representative of fundamentals. Second, we investigate factors that explain the dynamics of Brazilian real exchange rate at the pandemic period. We find the Balassa-Samuelson effect and the terms of trade have significant correlation with the exchange rate. Moreover, we note a decrease of the sensibility associated to Balassa-Samuelson and an increase of the terms of trade coefficient. Third, we show that the contributions of the Balassa-Samuelson effect and the terms of trade for the variation of the real exchange rate rose (in absolute values) in the Covid-19 crisis. However, these factors contributions present opposite signals: terms of trade induced appreciation and Balassa-Samuelson worked as a depreciation factor. Finally, we find that during the pandemic the exchange rate was more impacted by trade than by the financial sector.

Certainly, we are not the first to use equilibrium models to explain the dynamics of the Brazilian exchange rate. Some works have addressed this issue. Marçal, Pereira and Santos (2003) present evidences that the Purchasing Power Parity (PPP) does not hold for the Brazilian economy. Marçal (2012) compute the exchange rate misalignment for several countries including Brazil. He finds the Brazilian currency is the most overvalued in the sample of the study compared to fundamentals. Marçal et al. (2015) incorporate trade balance information on the BEER model. They use the proposed model to analyze the Brazilian case and conclude information regarding external accounts play a leading role to explain exchange rate misalignment. Finally, Pessôa and Ribeiro (2016) estimate the Fundamental Equilibrium Exchange Rate (FEER) and the BEER for Brazil. They find both models yields similar values for the equilibrium exchange rate. Our work differs from these studies at least in two key points. First, we analyze the contribution of the determinants during the pandemic, a time with no normal conditions that never happened before. Second, we test a number of different specifications of the model which provide more robustness for results.

The remainder of this paper is organized as follows. Section 2 presents the BEER/ECM model. Section 3 describes the data used to estimate the model. Section 4 discusses the results and Section 5 presents our final conclusions.

2 Methodology

Following Hambur et al. (2015), we use ECM to estimate the equilibrium level of Brazilian real exchange rate from a set of fundamentals. This approach belongs to the class of BEER models. In opposition to alternative methods for equilibrium exchange rate estimation, such as the FEER model, the BEER model overcomes some difficulties on the assessment of the long-run equilibrium path of the real exchange rate by obtaining it as the fitted value of a long-run relationship, without the need of making assumptions on the long-run values of the economic fundamentals. Unlike BEER models, FEER is a dynamic equilibrium model which requires many hypotheses related to external and domestic equilibrium and, therefore, imposes additional difficulties for an emerging economy such as the Brazilian one.

The economic theory supports the existence of a relationship between the equilibrium real exchange rate and variables that represents its long-run determinants. In this context, ECM becomes an appropriated tool to estimate equilibrium real exchange rate, as it disentangles the long-run relationship from the short-run fluctuations through a two-stage estimation. At ECM first stage, following MacDonald (2000), we assume a long-run equilibrium at current account and derive theoretically a cointegrating relation that represents the equilibrium real exchange rate equation. As in any cointegrating relation, it does not require stationarity for any variable, just for the resultant residuals. At ECM second stage, we consider the first differences of the variables presented at the first stage, the error correction factor, obtained as the first stage residuals, and additional variables that may help the real exchange rate to converge to its equilibrium value.

The coefficient of the error term extracted from the estimated cointegrating relationship and applied to an error-correction formulation assesses the speed of adjustment of real exchange rate toward its long-run equilibrium relation. This coefficient must be negative so that it pushes down the positive errors and up the negative ones, inducing convergence to the equilibrium level.

2.1 First stage

The cointegrating relationship we estimate is similar to the specification used in MacDonald (2000), Hambur et al. (2015) and Ribeiro et al. (2016). As previously explained, by assuming equilibrium at the current account, it is possible to obtain an expression that writes the equilibrium real exchange rate as a function of its long-run determinants. Based on this relation, the long-term determinants are the terms of trade (ToT), the interest rate differential between domestic and foreign interest rates, the net international investment position, the risk measure associated with the domestic economy, the Balassa-Samuelson effect, measured by the NTT variable which accounts for productivity differential between domestic and foreign economies, and the economic activity differential between domestic and foreign economic activity indexes.

We write the first stage as:

$$rer_t = c_0 + c_1 ToT_t + c_2 dif\_r_{t-1} + c_3 IIP_t + c_4 risk_t + c_5 NTT_t + c_6 dif\_GDP_t + u_t \qquad (1)$$

where rer is the real exchange rate, ToT is the terms of trade, dif_r is the interest rate differential, IIP is the net international investment position, $risk$ is a risk measure associated to the Brazilian economy (local market), NTT is the measure of the Balassa-Samuelson effect, dif_GDP is the activity differential and u is an error component.[3]

In order to estimate the first stage, we take the logarithms of each variable or their differences. These transformations do not intend to make series stationary. As a cointegrating relation, stationarity is not required for the regressors or for the dependent variable, but just for the resulting residuals.[4] Therefore, before estimating the second stage, we perform unit root tests on the first-stage residuals to guarantee this condition is met.

2.2 Second stage

At ECM second stage, we include additional variables that may help estimated real exchange rate to converge to its equilibrium value through short-run fluctuations. Short-run variables that may force real exchange rate to deviate from its equilibrium path include

[3] In Data section, we describe in details all variables used in this paper.

[4] See, for instance, Engle and Granger (1987).

a commodity price index and some variables that intend to capture risk sentiment and opportunities in global financial markets, such as the volatility and stock market indexes. We also consider in this stage the first differences of variables (in log) presented at the first stage, as opposed to their levels (in log) in order to account for shorter-term influences on the exchange rate. The first equation error term is also considered in the second stage equation, as it is inherent in the error correction model. The coefficient associated to the first-stage residuals must be negative to ensure long-term convergence to the equilibrium real exchange rate level. We also verify if this condition is met.

We write the second stage as:

$$\Delta rer_t = d_0\hat{u}_{t-1} + d_1\Delta rer_{t-1} + d_2ToT_t + d_3\Delta dif\_r_t + d_4\Delta IIP_t + d_5\Delta risk_t + d_6\Delta NTT_t + d_7\Delta dif\_GDP_t + d_8\Delta cmd_t + d_9\Delta cmd_{t-1} + d_{10}\Delta dif\_stock_t + d_{11}\Delta VIX_t + v_t \quad (2)$$

where *cmd* is the Commodity Research Bureau's commodity index, dif_stock is the stock indexes differential, defined as the difference between domestic and foreign stock market indexes, and VIX is the Cboe's volatility index.

3 Data

We use quarterly data to estimate both stages. The sample period spans 20 years of data, from the first quarter of 2002 to the last quarter of 2022. We discarded the period immediately after the Real monetary stabilization plan, introduced in July 1994, since one of its main pillars was a fix peg to the US-dollar, which lasted until the speculative attack occurred in January 1999. The attack forced the R$/US$ exchange rate devaluation and the subsequent adoption of the free-floating exchange rate regime and, in June of 1999, the implementation of the inflation-targeting regime as a new nominal anchor. In this section, we present a brief description of the variables used in this paper. In Appendix 1, we present relevant information about these variables and their respective formulas.

Since our aim is to study the behavior of the Brazilian real exchange rate during the pandemic period, we need to define the beginning and the end of the sanitary crisis. We adopt the period from the first quarter of 2020 to the last quarter of 2020 as the pandemic. Although the number of deaths due the Covid-19 was still high during the first quarter of 2021, we do not consider quarters from the end of 2020 onwards as mass vaccination started in January of 2021. Any quarter outside this non-vaccination period is called out-of-the-Pandemic period. We also analyze some alternatives to this definition and do not find qualitative changes in the results.

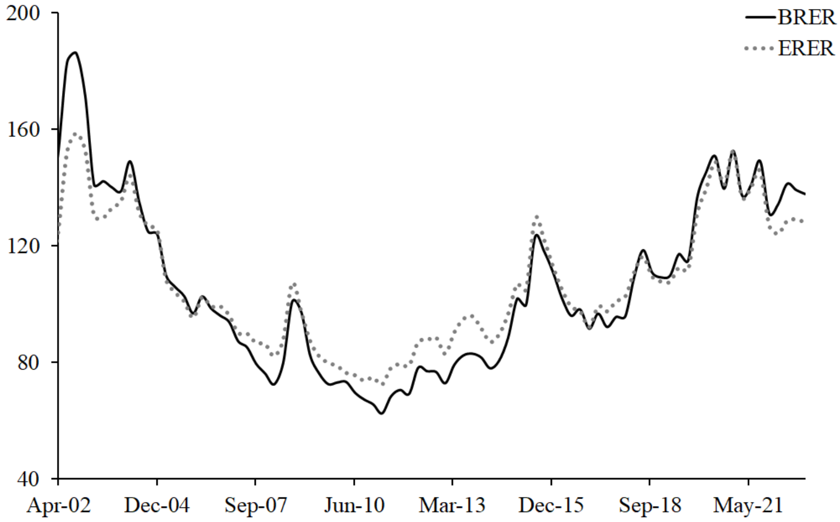
Some variables had to be constructed, either because they are not available in the frequency we needed or because we are dealing with relative, instead of absolute, versions of them. For those relative variables, we compare Brazil's position with the corresponding foreign position using two different concepts of real exchange rates: the bilateral real exchange rate (BRER) and effective real exchange rate (ERER). BRER consists of the nominal exchange rate corrected by the difference between domestic and foreign consumer price indexes. In this work, BRER is based on the US economy. ERER is a weighted average of bilateral real exchange rates computed for the fifteen most important Brazilian trading partners.[5] Both rates are computed by the Central Bank of Brazil. We use the same weights and countries to build some variables used on regressions that present the ERER as the dependent variable. For instance, we evaluate the GDP differential as the difference between the Brazilian and the US GDPs when the BRER is the dependent variable, but we replace it by the difference between the Brazilian GDP and a GDP weighted average of the fifteen most relevant Brazilian trading partners when ERER is considered. The same thing occurs to the interest rate differential and the stock market differential.

Figure 1 plots the evolution of these two real rates, where higher rates mean a more depreciated Brazilian currency. We note that bilateral and effective rates present similar patterns. The correlation between them reaches 97% during the studied period, which is expected since the US is the biggest economy in the world and the second largest trade partner of Brazil. Basically, both rates present an appreciation during the first half of the period and a depreciation afterward. They also are sensitive to the main episodes that affected Brazilian economy since 2000, namely the presidential election in 2002, the global financial crisis in 2008, the beginning of President Rousseff impeachment process in December 2015 and the Covid-19 crisis in 2020.

The Balassa−Samuelson effect is based on Couharde et al. (2018) and Couharde et al. (2020). It is measured by the variable NTT, which is defined by the productivity differential between tradable (T) and non-tradable (NT) goods sectors, understanding that the greater this differential, the greater the difference between the prices of non-tradable goods in relation to the prices of tradables. Balassa and Samuelson assume that, as tradable goods have their prices quoted in international market, these prices would be represented by producer price indexes, while non-tradables have their prices quoted only in domestic market. Both prices would be represented by consumer price indexes. We construct the NTT variable in relative rather than absolute terms, i.e., comparing Brazil's differential with the average differential of its main trading partners. Figure 2 plots the evolution of this measure in Brazil during the sample period. In general, we observe a decrease in the measure along the years, but with a sharp fall at the beginning of the pandemic. NTT negative shock in 2020 reflects an increase in service (non-tradable)

[5] In decreasing order of importance: China (at around 30% between 2012 and 2022), USA (20%), Argentina (9%), Germany (6%), Netherlands (5%), Japan (4%), Korea (4%), Chile (3%), Italy (3%), Mexico (3%), India (3%), France (3%), Spain (3%), United Kingdom (2%) and Belgium (1%).

Figure 1: Bilateral and effective real exchange rates



Notes: This figure shows the evolution of the bilateral and the effective real exchange rates in Brazil (quarterly data). The bilateral rate (BRER) is defined as the nominal exchange rate (R$/US$) corrected by the consumer price differential between the two currencies (IPCA-IBGE for Brazil and CPI for US). The effective rate (ERER) is defined as an average of bilateral real exchange rates selected from a basket of currencies from the main trade partners with Brazil, weighted by the share of each partner on Brazilian external trade. Higher rates mean a more depreciated Brazilian currency.

sector productivity due to severe dismissal of its predominantly more informal and unskilled workers, rather than to an increase in its production level. This productivity increase in non-tradable sector reduces the productivity differential between tradable and non-tradable goods, which leads to a reduced price differential between non-tradable and tradable goods and finally to a decreased NTT ratio.

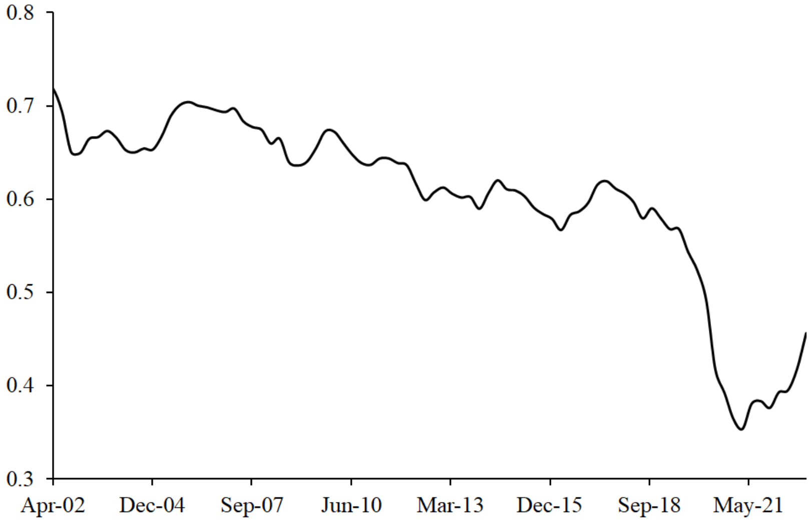
The negative shock on NTT, related to a change in labor market composition, avoided further real exchange rate appreciation from the positive shock that occurred in terms of trade (ToT), associated to a strong acceleration on iron ore prices (see Figure 3).

Finally, we construct a variable we called informality effect (see Appendix 1) and include it in the second stage. This effect works as a control for a possible change occurred in labor market composition during 2020/2021 pandemic period. We define it as the ratio between informal employed population and total employed population. Figure 4 presents the time evolution of the informality effect. We note a sharp fall of informal workers at the beginning of the pandemic period as well as a quick recovery.[6]

Some variables can be represented by several proxies. Instead of choosing a proxy to represent a variable, we prefer to alter the proxies on regressions. Thus, we have different specifications of the model. Each specification of the model is defined by a combination of regressors. Then, we evaluate the effects of a given variable through the distributions of their sensibility. For example, to capture the Brazilian risk (variable *risk*

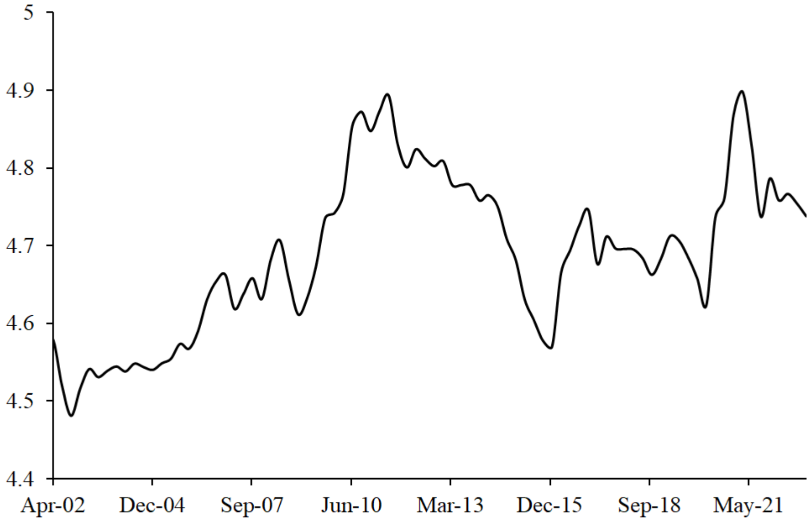
[6]More details about this variable are in the Appendix 1.

Figure 2: Balassa-Samuelson effect



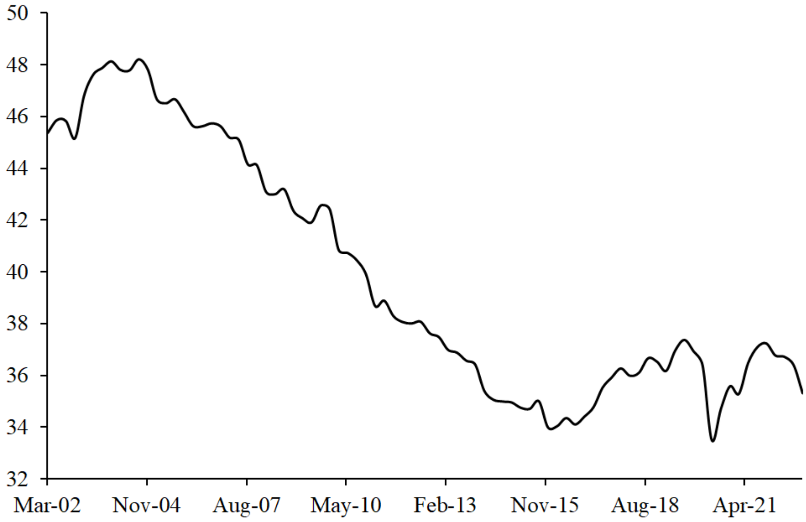
Notes: This figure shows the evolution of the BalassaSamuelson effect, measured here by the prices of non-tradable goods in relation to the prices of tradables for Brazil.

Figure 3: Terms of trade



Notes: This figure shows the evolution of terms of trade in Brazil.

Figure 4: Informality effect



Notes: This figure shows the evolution of informality effect in Brazil. We defined it as the proportion of informal workers on total labor force.

in Equations 1 and 2) we use some proxies based on transformations of the following variables: Consumer confidence index, Economic Policy Uncertainty Index for Brazil, Brazil 1-year CDS, Brazil 5-year CDS and FGV Economic Uncertainty Index (see Table A3 in Appendix 1). We believe this approach increases the robustness of our results. Not all versions are considered in the analysis since we discard those that do not generate stationary residuals on the first stage or that do not have a negative coefficient associated to the error correction factor on the second stage. Fortunately, based on this criterion, only a few specifications are rejected.

4 Results

Our main purpose in estimating the ECM model is to identify misalignments on the real exchange rate trajectory. We follow the misalignment as the difference between the observed real exchange rate and the path constructed from its determinants. Nevertheless, we differ from the traditional approach since we do not use the path fitted from a single model but the median path of all ECM specifications of the model considered.

Figure 5 presents the evolution of effective and bilateral real exchange rates (BRER and ERER) during the sample period, respectively, as well as estimated median path and a tunnel built on the maximum and minimum values of all specifications of the ECM model for each sample observation. We note a positive misalignment from 2002 to 2004. This period starts with the 2002 presidential election when uncertainties associated with the maintenance of the economic policies were appointed as the main cause of the exchange depreciation. There is a reversal in this pattern with the mitigation of the uncertainty after the new administration took office in 2003. During the subprime financial crisis, in 2008, exchange rate devaluation stayed below the path built on fundamentals. This finding coincides with a period of international confidence in the Brazilian economy due to the easing of the fiscal and external debt burden and improved growth, which made rating agencies to grant Brazil an investment-rate rating. During the political crisis in 2015, which culminated with the president impeachment, the exchange rate devaluation was above the median path derived from fundamentals, even though inside the maximum-minimum-value tunnel. In 2020, when the Covid pandemic started, we observe a sharp devaluation. Despite this sharp rise, the real exchange rate path followed its estimated median values and remained within the range delimited by maximum and minimum values of model trajectories based on equilibrium real exchange rate determinants during most of the pandemic period.

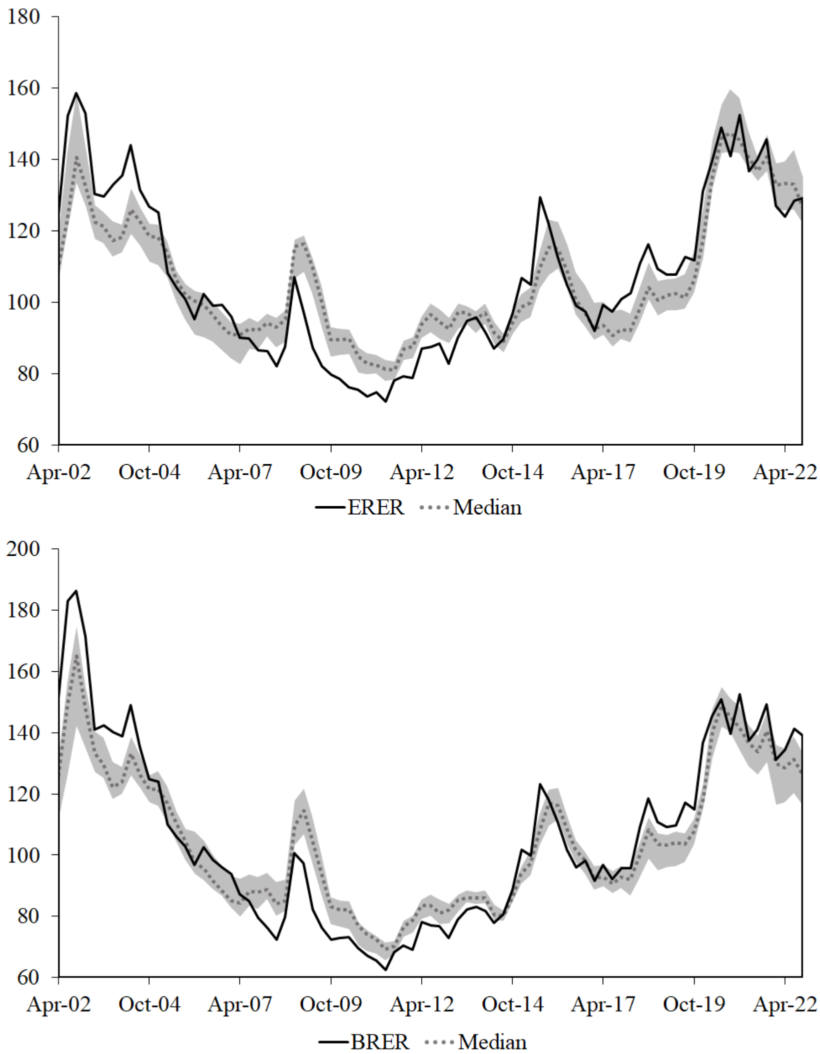
One special concern with our results is the use of the median, since it does not necessarily represent any specification of the model (the median can be an element out of the sample). This fact could undermine the economic interpretation of our results. However, we find that the correlation between the paths estimated by the model and the median is greater than 96%. Furthermore, 68% and 49% of the series fitted for BRER and ERER, respectively, are statistically no different from the median.[7] A graphical analysis shows a number of specifications have estimated exchange rate paths indistinguishable from the median.[8] Therefore, the use of the median does not compromise economic analysis since there are several versions of the model that barely differ from it.

Besides misalignment assessment, we use the methodology developed to identify factors that may explain the sharp devaluation of the real exchange rate. We focus our results on three main questions. First, we analyze which variables changed most during the pandemic. In order to answer this question, for each variable, we test if the mean observation during the pandemic is significatively different from the mean observation out of the pandemic period. Second, we evaluate whether the impact of the variables on the exchange has rate changed during the pandemic. For answering this question, we build two dummy variables - one takes the value one during the pandemic, while the other takes the value one out of the pandemic period. Thus, we split the sample period in two subsamples. We estimate all specifications of the model using the product of those dummies with the variable of interest. Therefore, the specifications of the model generate two coefficients - one for each subsample - for the variable of interest. This

[7] We implement the following test. For each specification of the model, let dif be the series defined by the difference between the fitted path and the median. Consider the regression $dif = c + \text{error}$, where c is a constant. The variance-covariance matrix was estimated using HAC in order to avoid misleading inference due to autocorrelated errors. Then, we study the significance of c.

[8] Since the curves are indistinguishable, we opt to not present the figure.

Figure 5: Equilibrium bilateral exchange rates



Notes: This figure presents the evolution of effective and bilateral real exchange rates (ERER and BRER) during the sample period, as well as estimated median and a tunnel built on the maximum and minimum values of all specifications of the model.

strategy makes possible to verify whether the coefficients are significatively different in each model and how they change in magnitude. We finally analyze the total contribution of a given variable for changes in the exchange rate. Our aim is to verify if the mean contribution, defined as the product of the model's coefficient and the variable of interest, during the pandemic is significatively different from that out of the pandemic period.

Considering how variables change during the pandemic, we obtain that, except for interest rate differentials, most of the variables used on the model presented important variations during the pandemic period. Clearly, the real exchange rates, both the ERER and the BRER, were the series that presented the most significant changes. Table A4 in Appendix 1 presents these variations, representing by M_P and $M_{\bar{P}}$ the mean of each vari-

Table 1: Mean of the coefficients of the second stage

Variable	Dependent Variable	c_P	χ_P (%)	$c_{\bar{P}}$	$\chi_{\bar{P}}$ (%)
NTT	ERER	-10.31	100	-14.08	100
	BRER	-6.63	100	-10.31	100
Risk	ERER	0.23	79.66	0.15	55.93
	BRER	0.27	92.59	0.23	96.29
IIP	ERER	0.01	0	0.07	59.32
	BRER	-0.02	0	0.05	37.93
ToT	ERER	-6.14	100	-3.02	100
	BRER	-4.23	100	-2.21	100

Notes: This table presents the mean of the coefficients of the second stage regression across all specifications. c_P and $c_{\bar{P}}$ are the mean of the coefficients of a variable of interest within and without the pandemic period. χ_P and $\chi_{\bar{P}}$ are the percentage of models with significant coefficients.

able during the pandemic and out of the pandemic period. For this result we considered the first difference of all variables, as they appear in the second stage.

In order to analyze how these changes are transmitted to the real exchange rate, we must take into account that the coefficients may have changed during the pandemic. Based on Table A4 in Appendix 1, we chose the real exchange rate's fundamentals that most changed. As specifications of the model differ on the regressors used, we normalized all proxies in order to analyze the results. Normalization makes the impact of a given variable in the real exchange rate comparable across specifications since the coefficient associated with the variable in each specification does not take into account the amplitude of the proxy's movement, carrying just the information on the transmission of the proxy's influence to the real exchange rate. Regarding the coefficients, we summarize our findings in Table 1.

Clearly, the Balassa-Samuelson effect (NTT) and the terms of trade (ToT) are important variables to explain real exchange rates' changes. They are significant in all specifications of the model. During the Covid pandemic, while we observe a reduction in the absolute value of the coefficient associated to NTT, we observe the opposite with the ToT. The histograms of those coefficients, presented in Appendix 2, confirm the shift occurred during the pandemic. Regarding the coefficient associated with the Brazilian risk, it clearly increased its influence both in magnitude and significance. However, the histograms do not show clearly a shift but just a bigger dispersion on data. The opposite occurs to the coefficient associated with international investment positions (*IIP*): it reduces both in magnitude and significance during the pandemic. These results suggest that during the pandemic the exchange rate suffered greater influence of trade than of financial sector. This evidence reinforces the idea that the exchange rate absorbed the impact of disruptions in the global supply chains and demand shocks during the coronavirus pandemic.

Finally, we compute the mean contribution of each variable that appears at the second stage within and without the Covid pandemic period - Cont_P and $\text{Cont}_{\bar{P}}$ - for the variation of BRER and ERER. Table 2 unequivocally shows the importance of NTT on real exchange rate. This result is by itself interesting because the Balassa-Samuelson effect is normally referred as being of minor importance.[9] As the Balassa-Samuelson effect is associated with productivity changes, this finding suggests that during the sample period the Brazilian economy suffered a productivity loss that led to a depreciation of the real exchange rate.

Table 2: Contribution of variables of the second stage

	Cont_P		$\text{Cont}_{\bar{P}}$	
	$ERER$	$BRER$	$ERER$	$BRER$
$d_0\hat{u}_{t-1}$	0.0017**	-0.0010**	0.0046	0.0038
$d_1\Delta rer_{t-1}$	-0.0013**	0.0062**	0.0014	0.0009
d_2ToT_t	-0.0644**	-0.0456**	-0.0049	-0.0035
$d_3\Delta dif\_r_t$	0.0069**	0.0042	-0.0015	-0.0008
$d_4\Delta IIP_t$	0.0156**	0.0101**	-0.0018	-0.0013
$d_5\Delta risk_t$	0.0021**	0.0268**	-0.0035	-0.0056
$d_6\Delta NTT_t$	0.4788**	0.3248**	0.0279	0.0189
$d_7\Delta dif\_GDP_t$	-0.0019**	-0.0118**	-0.0009	-0.0004
$d_8\Delta cmd_t$	-0.0169**	-0.0200**	-0.0065	-0.0077
$d_9\Delta cmd_{t-1}$	0.0043*	-0.0005	0.0038	-0.0005
$d_{10}\Delta dif\_stock_t$	-0.0047	-0.0039	-0.0050	-0.0001
$d_{11}\Delta VIX_t$	-0.0141**	-0.0006**	0.0010	0.0008

Notes: This table presents the contribution of each variable of the second stage within and without the Covid pandemic period - Cont_P and $\text{Cont}_{\bar{P}}$ - for the variation of BRER and ERER.

**Reject H_0: $\text{Cont}_{\bar{P}} = \text{Cont}_P$ at the 1% significance level. *Reject H_0: $\text{Cont}_{\bar{P}} = \text{Cont}_P$ at the 5% significance level.

During the Covid pandemic, most variables presented significant changes in their contributions. The importance of the Balassa-Samuelson effect is astonishing. Within this period, the mean contribution hikes from 0.0279 and 0.0189 for ERER and BRER respectively to 0.4788 and 0.3248. This result gives evidence of how strong was the productivity loss during the Covid pandemic, being the most important factor for the sharp depreciation observed in this period. It would be expected that a developing country, for being more dependent on labor, suffered an intense productivity loss during the pandemic, but the magnitude of the loss was surprising. The ToT also presented a great variation in the mean contribution, changing from -0.0049 and -0.0035 for ERER and BRER respectively to -0.0644 and -0.0456. However, ToT and NTT pushed the real exchange rate in

[9] For instance, see Engle (1999).

opposite directions. While ToT induced the appreciation the real exchange rate, the NTT has forced its depreciation.

In order to verify the robustness of these results, we added a variable that represents informality changes in the labor market at the second-stage regressions. Informality is related to productivity losses. Therefore, we wonder if adding informality as a control variable would mitigate the results for the Balassa-Samuelson effect. The results we obtained did not show any qualitative change. Informality does not appear significant in any specification of the model, while the Balassa-Samuelson effect remains significant in all of them.

5 Conclusion

Following a BEER approach for estimating Brazilian equilibrium real exchange rates, we identify some periods of misalignments in the last 20 years. The 2002 presidential election, the 2008 subprime crisis and the 2015 Brazilian political crisis are evidences of these misalignments.

Covid-19 crisis, along 2020, the non-vaccination period, had unprecedented structural effects on many areas and it was not different on exchange rates behavior and on their economic fundamentals. We observe a sharp real exchange rate depreciation along 2020. Despite this sharp rise, the real exchange rate path followed its estimated median values. It remained within the range delimited by maximum and minimum values of model trajectories based on equilibrium real exchange rate determinants during most of the pandemic period.

Covid-19 crisis was not similar to the others where uncertainty, lack of confidence, political risks and exclusively domestic aspects were most prominently involved. There were disruptions in the global supply chains and demand shocks during the coronavirus pandemic. These disruptions had structural impacts on economic fundamental measures, especially those related to prices and trade. Therefore, the Balassa-Samuelson productivity differential effect, measured here as the ratio of prices of non-tradable goods and prices of tradables, and the terms of trade, defined as the ratio of prices of exports and prices of imports, were severely hit. They explain most of real exchange rate changes over the pandemic period, being Balassa-Samuelson effect the most important driver in our model.

The shocks on BS and ToT measures were in different directions: BS decreased over 15% in 2020, while ToT increased 13%. The effect of BS shock on the real exchange rate depreciation was not even greater because of the ToT shock was in opposite direction. This evidence reinforces the idea that real exchange rate has absorbed the impact of the disruptions and, therefore, that it was not severely misaligned with respect to the fundamental variables during the pandemic.

References

Balassa, B. (1964). The purchasing power parity doctrine: a reappraisal. *Journal of Political Economy*, 72 (6), 584-596.

Chen Y., K. Rogoff and B. Rossi (2010). Can exchange rates forecast commodity prices? *The Quarterly Journal of Economics*, 125 (3), 1145-1194.

Couharde, C., A. Delatte, C. Grekou, V. Mignon and F. Morvillier (2018). EQCHANGE: A world database on actual and equilibrium effective exchange rates. *International Economics*, 156, 206-230.

Couharde, C., A. Delatte, C. Grekou, V. Mignon and F. Morvillier (2020). Measuring the Balassa-Samuelson effect: a guidance note on the RPROD database. *International Economics*, 161, 237-247.

Engel, C. (1999). Accounting for U.S. real exchange rate changes. *Journal of Political Economy*, 107 (3), 507-538.

Engle, R. and C. Granger (1987). Cointegration and error correction: representation, estimation and testing. *Econometrica*, 55 (2), 251-276.

Hambur, J., L. Cockerell, C. Potter, P. Smith and M. Wright (2015). Modelling the Australian Dollar. *RBA Research Discussion Papers, Reserve Bank of Australia*, 2015-12.

MacDonald, R. (2000). Concepts to calculate equilibrium exchange rates: an overview. *Discussion Paper Series 1: Economic Studies, Deutsche Bundesbank*, 3.

Marçal, E. (2012). Estimando o desalinhamento cambial para países selecionados utilizando análise baseada em fundamentos, Nota Dinte 10, Instituto de Pesquisa Econômica Aplicada (Ipea).

Marçal, E., O. Santos and P. Pereira (2003). Paridade do poder de compra: testando dados brasileiros. *Revista Brasileira de Economia*, 57 (1), 159-190.

Marçal, E., B. Zimmermann, D. de Prince and G. Merlin (2015). Addressing important econometric issues on how to construct theoretical based exchange rate misalignment estimates. *Textos para discussão*, 401, FGV EESP-Escola de Economia de São Paulo, Fundação Getulio Vargas (Brazil).

Ribeiro, L. and Pessôa, S. (2016). Modelos de câmbio real para a economia brasileira. Nota Técnica, FGV/IBRE.

Samuelson, P. A. (1964). Theoretical notes on trade problems. *Review of Economics and Statistics*, 46 (2), 145-154.

Appendix 1

In this Appendix we show how we define the variables presented in regressions (1) and (2). Table A1 lists the primary series we use.

Table A1: Primary series

Nº	Series description	Source
s_1	Bilateral real exchange rate (BRER)	BCB-SGS[1] (series Nº 11753)
s_2	Effective real exchange rate (ERER)	BCB-SGS (series Nº 11752)
s_3	Terms of trade (ToT)	FUNCEX[2]
s_4	Brazilian federal funds rate	Bloomberg (BZSELICA index)
s_5	US federal funds rate	Bloomberg
s_6	Wu-Xia shadow federal funds rate	Atlanta FED[3]
s_7	BRL-USD Interest Rate Spread	Bloomberg (BRLUSDIS CMPN Curncy)
s_8	Commodity Research Bureau index	Bloomberg (CRB CMDT Index)
s_9	Commodity Research Bureau food index	Bloomberg (CRB FOOD Index)
s_{10}	Commodity Research Bureau metal goods index	CRB METL Index
s_{11}	International investment position/GDP	BCB-SGS (series Nº 12506)
s_{12}	Net International Investment Position	BCB-SGS (series Nº 24010)
s_{13}	Consumer confidence index	BCB-SGS (series Nº 4393)
s_{14}	Economic Policy Uncertainty Index for Brazil	web site[4]
s_{15}	Brazil 1-year CDS	Bloomberg (Brazil CDS USD sr 1y d14 Curncy)
s_{16}	Brazil 5-year CDS	Bloomberg (Brazil CDS USD sr 5y d14 Curncy)
s_{17}	FGV Economic Uncertainty Index	Bloomberg (FGVUIEBR Index)
s_{18}	Cboe Volatility Index	Bloomberg (VIX Index)
s_{19}	Brazilian GDP	IBGE[5]
s_{20}	US GDP	FRED[6]
s_{21}	IBOVESPA	B3[7]

Notes:
[1] www3.bcb.gov.br
[2] www.funcexdata.com.br
[3] www.atlantafed.org
[4] www.policyuncertainty.com
[5] sidra.ibge.gov.br
[6] fred.stlouisfed.org
[7] b3.com.br

Table A2 lists the series we built.

Table A2: Built series

Nº	Description	
b_1	Balassa-Samuelson Effect (NTT)	Defined below
b_2	Stock-Market average index	$\sum_{i=1}^{15} w_i \ln(StockMarketIndex_i)$
b_3	Gross Domestic Product average index	$\sum_{i=1}^{15} w_i \ln(GDP_i)$
b_4	Interest Rate Average Index	$\sum_{i=1}^{15} w_i \ln(1+r_i)$
b_5	Informality index	Defined below

- Balassa-Sanuelson effect (NTT)

$$NTT_t = (cpi_t - ppi_t) - \sum_{i=1}^{15} w_{i,t}((cpi_{i,t} - ppi_{i,t}) \tag{3}$$

where t is time measured in quarters, i is the i^{th} trading partner in the rol of the 15 most important Brazilian trade partners, cpi is the Brazilian consumer price index in log terms measured by IPCA/IBGE, ppi is the Brazilian production price index in log terms measured by IPA-DI/FGV[10], and w_i is the weight of the i^{th} trading partner in Brazilian external trade.

Each trading partner's weight is defined as

$$w_{i,t} = \frac{M_t}{M_t + X_t} * w_{i,t}^{Imp} + \frac{X_t}{M_t + X_t} * w_{i,t}^{Exp} \tag{4}$$

where X is FOB total Brazilian exports to trading partners in US millions and M is CIF total Brazilian imports from trading partners in US millions obtained at Direction of Trade Statistics IMF Data. Besides, partial weights for imports and exports are:

$$w_{i,t}^{Imp} = \frac{M_t^i}{M_t} \tag{5}$$

and

$$w_{i,t}^{Exp} = \frac{X_t^i}{X_t} \tag{6}$$

- Informality effect

$$Inf\_effect_t = \frac{EP\_no\_contract_t + SelfEmployed_t + Employers_t}{EP\_formal_t + EP\_no\_contract_t + SelfEmployed_t + Employers_t} \tag{7}$$

[10]www.ipeadata.gov.br

where Inf_effect (Informality effect) is the proportion of informal employed population in total employed population in Brazil, $EP\_no\_contract$ is the employed population without a formal work contract, EP_formal is the employed population with a formal work contract, $SelfEmployed$ is the population employed by its own means and $Employers$ is the population that runs its own business. These data were obtained from Monthly Employment Survey (PME) of IBGE.

From the framework above, we define the variables used in regressions (1) and (2). Table A3 presents these definitions. In the text, we refer to p_1 and p_2 as BRER and ERER.

Table A3: Regressors

Variable	N°	Proxy	Variable	N°	Proxy
rer	p_1	$n(\ln(s_1))$	$risk$	p_{13}	$n(-\ln(s_{13}))$
rer	p_2	$n(\ln(s_2))$	$risk$	p_{14}	$n(\ln(s_{14}))$
dif_r	p_3	$n(\ln(s_4)-\ln(s_5))$	$risk$	p_{15}	$n(\ln(s_{15}))$
dif_r	p_4	$n(\ln(s_7))$	$risk$	p_{16}	$n(\ln(s_{16}))$
dif_r	p_5	$n(\ln(s_4)-\ln(b_4))$	$risk$	p_{17}	$n(\ln(s_{17}))$
dif_r	p_6	$n(\ln(s_4)-\ln(s_6))$	tot	p_{18}	$\ln(s_3)$
IIP	p_7	$n(s_{11})$	VIX	p_{19}	$\ln(s_{18})$
IIP	p_8	$n(s_{12})$	NTT	p_{20}	$\ln(b_1)$
IIP	p_9	$n(s_{11}.s_{19})$	dif_GDP	p_{21}	$\ln(s_4)-\ln(s_{20})$
cmd	p_{10}	$n(\ln(s_8))$	dif_GDP	p_{22}	$\ln(s_4)-\ln(b_3)$
cmd	p_{11}	$n(\ln(s_9))$	dif_stock	p_{23}	$\ln(s_3)$
cmd	p_{12}	$n(\ln(s_{10}))$	dif_stock	p_{24}	$\ln(b_3)$

Notes: $n(\cdot)$ is a normalizing function, i.e., $n(x) = \frac{(x-mean(x))}{st.dev(x)}$

Table A4: Percentage variation and p-value

Variable	M_P	$M_{\bar{P}}$	$P = \frac{M_P - M_{\bar{P}}}{M_{\bar{P}}}$	p-value
$\Delta(p_1)$	0.223722	0.000543	411.1506	0.0000
$\Delta(p_2)$	0.338224	−0.000104	3246.300	0.0000
$\Delta(p_3)$	−0.058413	−0.004052	13.41630	0.1359
$\Delta(p_4)$	−0.084639	0.037792	3.239577	0.0028
$\Delta(p_5)$	−0.038019	−0.012252	2.103107	0.7963
$\Delta(p_6)$	−0.031861	−0.005452	4.844146	0.4573
$\Delta(p_7)$	0.123064	0.006495	17.94737	0.1527
$\Delta(p_8)$	0.276330	−0.043938	7.289083	0.0000
$\Delta(p_9)$	0.163303	−0.031631	6.162705	0.0472
$\Delta(p_{10})$	0.093936	0.034088	1.755700	0.0183
$\Delta(p_{11})$	0.088904	0.032262	1.755700	0.0183
$\Delta(p_{12})$	0.043413	0.015754	1.755700	0.0183
$\Delta(p_{13})$	0.109724	−0.017640	7.220006	0.0080
$\Delta(p_{14})$	0.267691	0.017439	14.34984	0.0177
$\Delta(p_{15})$	0.084887	−0.023880	4.554727	0.0522
$\Delta(p_{16})$	0.139428	−0.029043	5.800791	0.0001
$\Delta(p_{17})$	0.404522	0.003643	110.0333	0.0000
$\Delta(p_{18})$	0.019112	0.001332	13.34394	0.0000
$\Delta(p_{19})$	0.125337	−0.006989	18.93338	0.0001
$\Delta(p_{20})$	−0.037791	−0.002241	15.86370	0.0000
$\Delta(p_{21})$	0.002858	0.000446	5.404161	0.0515
$\Delta(p_{22})$	−0.010975	−0.004685	1.342554	0.0371
$\Delta(p_{23})$	0.037662	0.009082	3.146715	0.0016
$\Delta(p_{24})$	0.012375	0.011246	0.100393	0.8908

Notes: M_P and $M_{\bar{P}}$represent the mean in and out the pandemic period respectively.

Table A4 presents the percentage variation of each variable p defined above in and out the pandemic period.

Appendix 2

In this Appendix we show the histograms of the coefficients of the second stage regression. Figure A1 presents the histogram when BRER is the dependent variable. Figure A2 presents the histogram when ERER is the dependent variable. Finally, Figure A3 is a joint histogram of BRER and ERER.

Figure A1: Histogram of regressors when BRER is the dependent variable

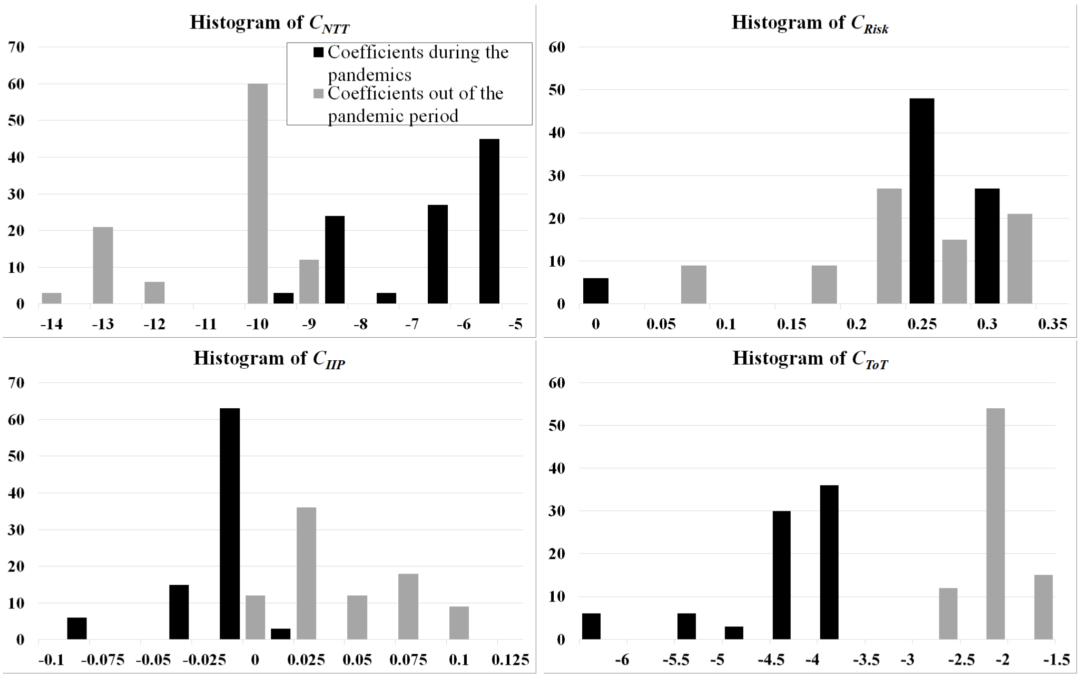


Figure A2: Histogram of regressors when ERER is the dependent variable

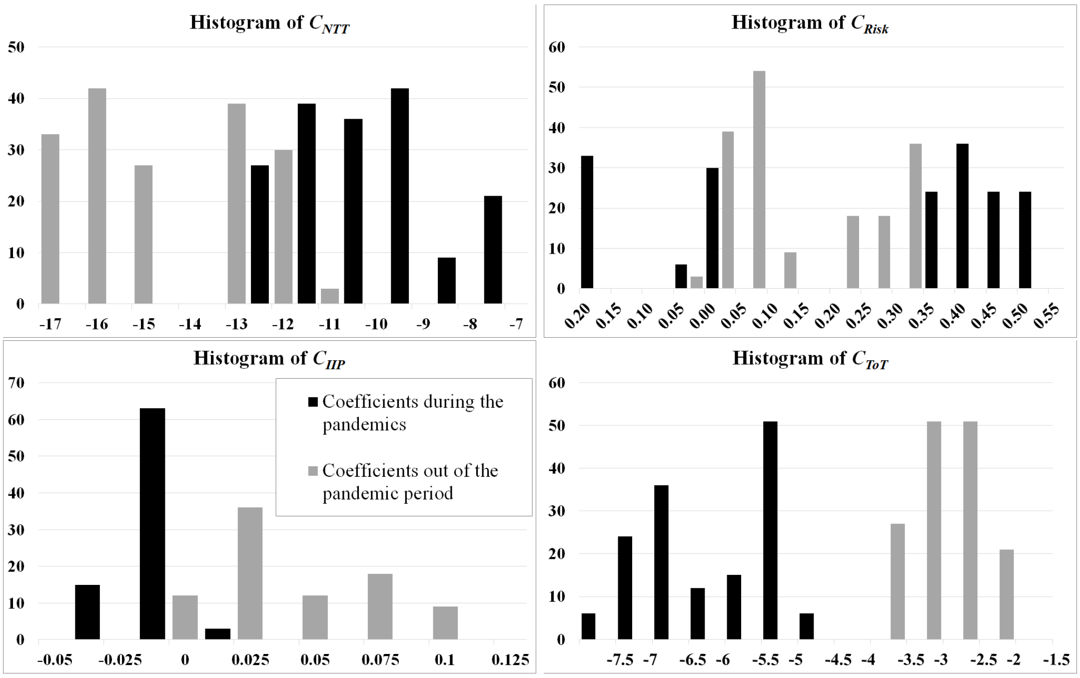


Figure A3: Joint histogram of regressors when BRER and ERER are dependent variables