Food Inflation During the Covid-19 Pandemic. A Comparison Between Brazilian and Thai Food Inflation During the Years 2020 and 2021.

Mrs. Lilian Cordeiro Prates

A Thesis Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Arts in Business and Managerial Economics
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เงินเฟ้อด้านอาหารในช่วงโควิด-19 ระบาด. การเปรียบเทียบ
ระหว่างอัตราเงินเฟ้ออาหารบราซิลและอาหารไทยในช่วงปี 2563 และปี 2564

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วิทยานิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาศิลปศาสตรมหาบัณฑิต
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By	Mrs. Lilian Cordeiro Prates
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Thesis Advisor	NIPIT WONGPUNYA

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ไทยและบราซิลเป็นผู้ส่งออกสินค้าเกษตรสุทธิที่โดดเด่น 2 ราย และทั้งสองประเทศได้รับผลกระทบอย่างรุนแรงจากการระบาดของโควิด-19 ในขณะที่ GDP ของไทยลดลง 6.1% ในปี 2020 เศรษฐกิจบราซิลหดตัว 4.1% แม้จะมีความคล้ายคลึงกันเหล่านี้ แต่ในช่วงระยะเฉียบพลันของการระบาดใหญ่ ราคาอาหารในบราซิลเริ่มเพิ่มขึ้นอย่างรวดเร็ว ในขณะที่ในประเทศไทย ราคาอาหารยังคงต่ำและคงที่ ในปี 2020 อัตราเงินเฟ้อด้านอาหารประจำปีในบราซิลอยู่ที่ 14,11% และของไทยอยู่ที่ 1.37% ดังนั้น การศึกษานี้จึงมีวัตถุประสงค์เพื่อสนับสนุนวรรณกรรมโดยการเติมเต็มช่องว่างข้อมูลเกี่ยวกับการเปลี่ยนแปลงของอัตราเงินเฟ้อของอาหารในสองประเทศดังกล่าวในช่วงการระบาดใหญ่ของโควิด-19.วิธีการ Autoregressive Distributed Lag ถูกนำไปใช้กับตัวแปรอธิบายที่เป็นไปได้ 13 ตัว ได้แก่ การนำเข้าอาหาร การส่งออกอาหาร อัตราดอกเบี้ย พร็อกซีสำหรับ DGP รายเดือน (หนึ่งรายการสำหรับแต่ละประเทศ) ดัชนีน้ำมันดิบ ราคาน้ำมันดิบ ดัชนีอาหารโลก อัตราแลกเปลี่ยน ค่าที่กำหนด อัตราแลกเปลี่ยนที่แท้จริง ดัชนีราคาสินค้าเกษตร ดัชนีผลผลิตทางการเกษตร และอัตราเงินเฟ้อพลังงาน จาก 13 ตัวแปรเหล่านี้ มีเพียง 6 ตัวแปรสุดท้ายเท่านั้น ที่มีนัยสำคัญ ทางสถิติ เหตุผลหลักที่ทำให้อัตราเงินเฟ้อด้านอาหารสูงขึ้นในบราซิลคือ: i) ประเทศนี้ไม่ได้ใช้ประโยชน์จากการตกต่ำของน้ำมันดิบระหว่างประเทศเพื่อให้ส่วนลดที่รุนแรงมากขึ้นในราคาพลังงานในประเทศ; ii) ความชะงักงันของการเติบโตของการผลิตสำหรับอาหารหลักบางชนิด; iii) การส่งผ่านสูงจากดัชนีราคาสินค้าเกษตรไปยังดัชนีราคาผู้บริโภค; และ iv) การลดค่าสกลเงินจำนวนมาก.

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Lilian Cordeiro Prates : Food Inflation During the Covid-19 Pandemic. A ComparisonBetween Brazilian and Thai Food Inflation During the Years 2020and 2021.. Advisor: NIPIT WONGPUNYA

Thailand and Brazil are two prominent net agro-exporters, and both countries were hit severely by the Pandemic of Covid-19. While Thailand's GDP decreased by 6.1% in 2020, the Brazilian economy shrank by 4.1%. Despite these similarities, during the acute phase of the pandemic, food prices in Brazil started to increase at an accelerated pace while, in Thailand, food prices remained low and stable. In 2020, the annual food inflation in Brazil was 14,11%, and Thailand's was 1.37%. Therefore, this study aims to contribute to the literature by filling the information gap about food inflation dynamics in those two countries during the Covid-19 pandemic. The Autoregressive Distributed Lag methodology was applied to 13 potential explanatory variables: Food Imports, Food Exports, Interest Rate, a proxy for Monthly DGP (one for each country), Crude Oil Index, Crude Oil Price, Global Food Index, Exchange Rate, Nominal Effective Exchange Rate, Agricultural Price Index, Agricultural Production Index, and Energy Inflation. Out of these 13 variables, only the last six were statistically significant. The key reasons for the food inflation hike in Brazil were: i) the country has not taken advantage of the international crude oil slump to provide more aggressive discounts in domestic energy prices; ii) the production growth stagnation for some staple foods; iii) high pass-through from Agricultural Price Index to Consumer Price Index; and iv) large currency devaluation.

Field of Study:	Business and Managerial Economics	Student's Signature ....
Academic Year:	2022	Advisor's Signature ....

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I could not have completed this journey without my husband's emotional support. I am also grateful to Trina for helping me to care for my children while this work was being written.

Lilian Cordeiro Prates

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Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:22
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTIR LNTAPROD
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.187137	0.147457	1.269091	0.2114
DIFLNTIR	0.533530	0.685300	0.778535	0.4406
LNTAPROD	-0.122173	0.218167	-0.559998	0.5785
LNTAPROD(-1)	-0.292253	0.223281	-1.308901	0.1977
C	2.134260	1.214939	1.756682	0.0863

R-squared	0.112809	Mean dependent var	0.106170
Adjusted R-squared	0.028314	S.D. dependent var	0.400530
S.E. of regression	0.394819	Akaike info criterion	1.079508
Sum squared resid	6.547039	Schwarz criterion	1.276333
Log likelihood	-20.36845	Hannan-Quinn criter.	1.153575
F-statistic	1.335100	Durbin-Watson stat	1.880959
Prob(F-statistic)	0.272812		

*Note: p-values and any subsequent tests do not account for model selection.

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CHAPTER 01

INTRODUCTION

Common sense suggests that countries with food sovereignty and an expressive positive trade balance of food and agri-based products are able to control the price of these commodities. Since they do not rely on imports, they are less susceptible to international price pressure. After the shock caused by the Covid-19 situation, Thailand and Brazil had different performances regarding the controlling of food inflation, despite their similarities. This chapter will encompass an overview of food inflation behavior during the Covid-19 Pandemic (2020 and 2021). It will be divided into four sections. The first section will be the Problem Statement, presenting the elements that raised inquiries about different outcomes of Thai and Brazilian food inflation. The second part will set forth the Research Question. The third part will present the justification and expected benefits of the research. Finally, the fourth section will discuss its limitations.

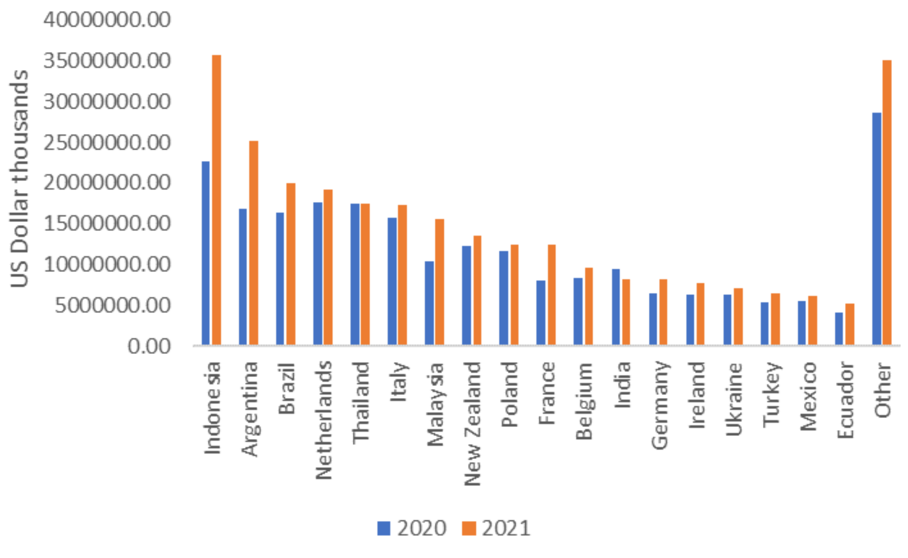
1.1 Problem Statement

Both Thailand and Brazil can be defined as big countries in terms of food and agri-based production. For its turn, Thailand has long been referred to as 'the kitchen of the world'. With its abundant natural resources, it is considered "one of the largest net food-exporting countries globally and (has become the 3rd food exporter in Asia after the big giants, China, and India". (WANG et al., 2020, pg. 02). "The country has one of the most advanced food processing industries in Southeast Asia, and its food and beverage sector is the country's third-largest industry" (Food Export Association of the Midwest USA and Food Export USA – Northeast (n.d.)). The abundance of raw materials, a skilled and affordable workforce, and a good logistics system make Thailand an important power at exporting processed food. "The development of these industries dates back to the 1960s when Thailand drafted its first National Economic and Social Development Plan. Within this strategy, the Government emphasized the food industry as a means to increase the value of cheap and abundant agricultural goods while taking advantage of relatively cheap labor wages." (THAMMACHOTE & TROCHIM, 2021, PG. 07).

Thailand is a recognized commodities exporter, but "from 1998 to 2016, processed food exports accounted for 60% of the agri-food sector … the processed food industry has replaced some traditional commodities, such as sugar and rice. Moreover, food processing is a labor-intensive activity that contributes to lowering the unemployment in Thailand, raising the average salary more than threefold from 1998 to 2016" (TANRATTANAPHONG et al., 2020). From the analysis during that period, the authors reported an interesting finding: Thai processed food is treated as a necessity good by developed countries (when income fall, the consumption rise) and luxury good by developing countries (when income fall, the consumption rise). Therefore, for a developed country, its GDP and the amount of Thai processed food export (TPFE) are negatively related (negative elasticity, moving in the opposite direction). Conversely, for the developing countries, their GDP and TPFE has positive elasticity; they move together. (TANRATTANAPHONG, et al. 2020). In this way, economic crises tend to lead to an improvement in TPFE towards developed countries.

Even during the Covid-19 Pandemic, with all constraints faced for the export sector, such as containers shortage since the 2Q2020, the increasing freight rate, and workforce shortage caused by the Covid-19 Pandemic, Thailand is still within the 15 more prominent food exporters and within the 5 food net-exporters. During the biennial of 2020 and 2021, Thailand exported more than US$ 17 billion each year in Processed Food and Agri-based products. The figures reached the order of US$ 17,465,088,000.00, in 2020 and US$ 17,418,353,000.00, in 2021, according to the database of the International Trade Center (ITC, 2022).

Figure 1 - *List of net exporting markets for the selected product group. Product group: Processed food and agro-based product*



Note: Data from: International Trade Center (ITC) database. Retrieved by: https://www.trademap.org.

Table 1, below, shows the main groups present in Thailand's trade import, regarding processed food and Agri-based category. The products with more preponderance were those for feedstuff preparations: Oilcake and Preparation for animal feeding, together encompassed 17,24% in 2020 and 20,70% in 2021. Around 60% of the processed food imports were spread throughout hundreds of other categories in 2020 and 2021.

Table 1 - *Thailand Processed Food and Agri-based Products Imports*

CATEGORY	2020	2021	2020%	2021%
Oilcake and other solid residues, fit for feed ingredient	1,013,225.00	1,359,521.00	12.38%	15.40%
Food preparations, n.e.s.	807,195.00	868,435.00	9.86%	9.84%
Preparations of a kind used in animal feeding	398,331.00	467,151.00	4.87%	5.29%
Cuttlefish and squid, frozen, with or without shell	386,319.00	381,845.00	4.72%	4.33%
Mixtures of odoriferous substances (used as raw material in the industry)	650,359.00	693,541.00	7.94%	%7.86
OTHER	4,930,463.00	5,055,617.00	60.23%	57.28%
TOTAL	8,185,892.00	8,826,110.00	100.00%	100.00%

Note: Author's calculations. Data from: International Trade Center (ITC)
https://www.trademap.org
The amount is in Thousands of US$

Likewise, Brazil is one of the most significant food exporters globally. In 2020, the country had more than US$ 15 billion (US$15,035,845,000.00) of processed food net exports. And during 2021, this figure reached almost US$20 billion (US$19,960,504,000.00) (ITC, 2022b). The figures below reflect only part of the huge Brazilian agricultural trade balance compound and refer specifically to processed foods. However, the Brazilian numbers hiked when the data extracted from ITC (2022b) was aggregated, considering F&B[1] in general and F&B production inputs. For F&B and its inputs, the trade balance was US$ 63.372.316.000.00 in 2020 and US$

70,949,842,000.00 in 2021.

Table 2 - *Brazilian F&B and F&B input main imports 2020 - 2021*

Categories	2020	2021	Ratio - 2020	Ratio - 2021
Fertilizers'	8,027,716.00	15,164,542.00	41.84%	53.75%
Cereals	2,108,189.00	2,878,426.00	10.99%	10.2%
Animal or vegetable fats and oils and their cleavage products; prepared edible fats; animal ...	1,226,397.00	1,591,466.00	6.39%	5.64%
Fish and crustaceans, molluscs, and other aquatic invertebrates	858,945.00	1,146,122.00	4.48%	4.06%
Other	6,964,611.00	7,432,925.00	36.3%	26.35%

Note: Autor's calculation. Data from: https://www.trademap.org
Values are in Thousands of US$

According to the Food and Agricultural Organization (FAO, 1999), "Since 1970, Brazil has been expanding agricultural production, and the country has gone from being an important importer to one of the world's leading food exporters." (Oliveira et al., 2019, pg. 2906). Nevertheless, the country still depends on the imports of milk and wheat.

[1] Unless otherwise stated, F&B circumscribes F&B consumed in-home or outside the home

As stated by the Brazilian Association of Food Industries (ABIA,2016), "the food and beverage industry is considered the largest national sector of the Brazilian transformation industry." (ARISSETO-BRAGOTTO et al., 2017). The national industry processed 58% of the total agricultural production, and processed food accounted for 51% of the agribusiness exports and 18% of the total Brazilian export." (ARISSETO-BRAGOTTO et al., 2017). The consumers' behaviors have been changed, from fresh to processed food. Currently, 85 percent of the food consumed in Brazil is processed, compared to 56% in 1980. (ABIA, 2013, as cited in Oliveira et al, 2019, pg. 2907)

"In 2020, Brazil kept as the main supplier for livestock products, highlighting soybean, animal protein, sugar, and coffee. In addition, the wheat crops had a markable production increase, which reduced the pressure to import this commodity." (IPEA, 2021).

The whole agricultural sector in Brazil exported US$ 100,701,953,630.00 and imported US$ 13,054,347,989, therefore the net exports of US$ 87,647,605,641, according to the Ministry of Agriculture, Livestock and Food Supply - MAPA (2022). For 2021, the amounts are still more impressive; the Brazilian agricultural sector had a trade surplus of US$ 104,992,957,229.00, the imports were US$ 120,521,447,545, and exports were US$ 15,528,490,316. This data was extracted from the Brazilian governmental system - AGROSTAT (MAPA, 2022), and differently from the values in table 03, encompasses all kinds of agrarian products, even not related to Food and Beverage (F&B), but excludes fertilizers.

The information in tables 1 and 2, from the International Trade Center (ITC) – a multilateral agency, displays some discrepancy compared to the information in the respective national statistics systems since each country compounds the items to reflect the idiosyncrasies of their economies. Nevertheless, the advantage of using the ITC data is the possibility of comparing the trade balance that contains the exact specification.

Nevertheless, despite having robust agribusiness environments and developed F&B production systems, neither of the countries studied here is self-sufficient in F&B and food production inputs. Tables 03 and 04 gather the main products imported by Brazil and Thailand. It is essential to put these products in evidence because they can be a key variable in explaining the F&B's price pressures. Moreover, they can provide clues to understanding the weaknesses in Thailand and Brazilian food sovereignty.

Table 3 - *Thailand F&B and F&B input main imports 2020 - 2021*

CATEGORIES	2020	2021	Ratio - 2020	Ratio - 2021
Fish and crustaceans, molluscs and other aquatic …	3,309,496.00	3,225,038.00	19.06%	18.08%
Residues from the food industries; prepared animal fodder…	2,285,110.00	2,033,469.00	13.16%	11.4%
Oil seeds; miscellaneous grains…	1,520,996.00	1,865,274.00	8.76%	10.46%
Fertilisers	168,9076.00	1,528,362.00	9.73%	8.57%

Table 3 - *Thailand F&B and F&B input main imports 2020 - 2021*

CATEGORIES	2020	2021	Ratio - 2020	Ratio - 2021
Cereals	1,074,417.00	1,271,019.00	6.19%	7.12%
Edible fruit and nuts;	916,042.00	1,152,923.00	5.28%	6.46%
Miscellaneous edible preparations	961,939.00	1,111,657.00	5.54%	6.23%
Edible vegetables and certain roots and tubers	980,401.00	975,309.00	5.65%	5.47%
Dairy produce; birds' eggs; natural honey...	728,635.00	724,753.00	4.2%	4.06%
Others	3,897,419.00	3,952,865.00	22.43%	22.15%

Note:Autor's calculation. Data from ITC. Retrieved from: https://www.trademap.org
Values are in Thousands of US$

Table 4 - *Mailing F&B Brazilian imports products in 2020*

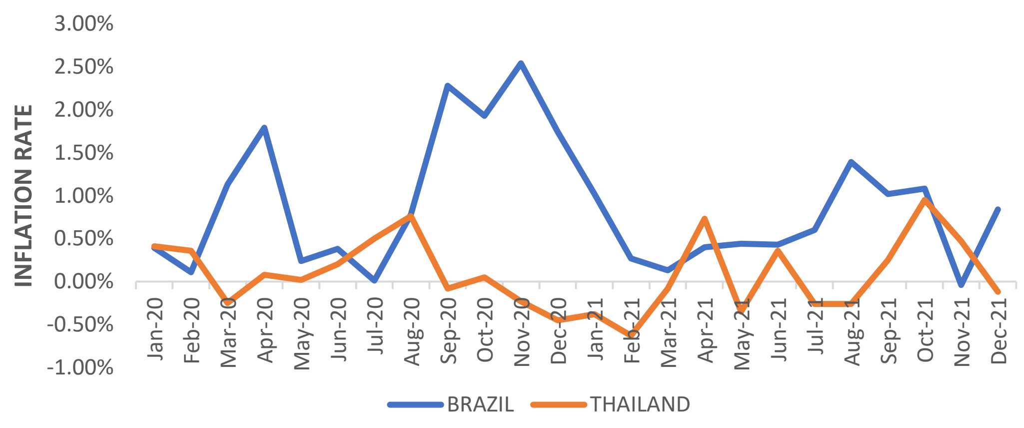
CATEGORY	Value in USD	Imports ratio
Cereal, flours, food preparations	3,902,869,385.00	25.13%
Oilseeds (ex. Soy)	1,414,706,437.00	9.11%
Fishery products	1,180,599,104.00	7.60%
Beverages	891,501,702.00	5.74%

Note. Data from MAPA (Ministry of Agriculture Livestock and Food Supply). https://indicadores.agricultura.gov.br/agrostat/index.htm

According to ITC (2022c), Brazil and Thailand occupy the 4th and 5th positions regarding net exports of Food and Agri-based products. Although these two countries are food self-sufficient and have suffered economic contraction from COVID-19, we can observe different outcomes if we analyze the F&B inflation.

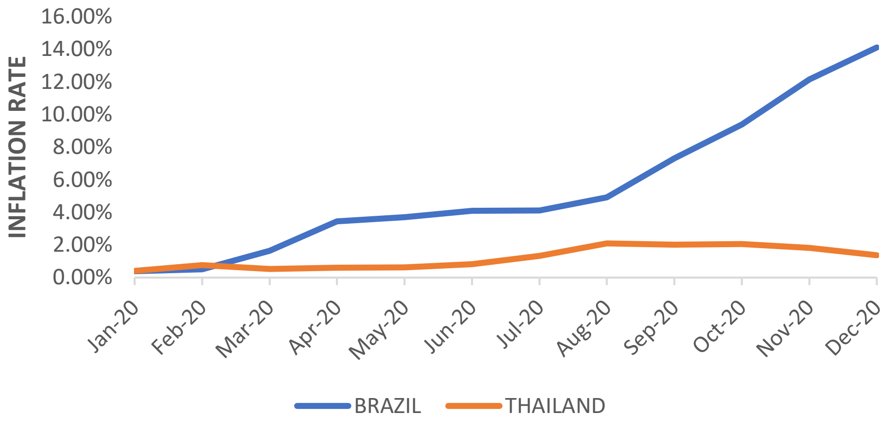
In January 2020, as shown in figure 02, the F&B inflation was 0.39 and 0.41% in Thailand and Brazil, respectively. Somehow the gap becomes more prominent as the months pass, reaching, by the end of the year, the accumulated value of 14,11% (Brazil) and 1.37%(Thailand). For the year 2021, the gap persists. Looking at the data from January until December, the Brazilian accumulated inflation was 7.94%, while Thailand was 0.67%, as shown in figures 03 and 04.

Figure 2 - *F&B Monthly Inflation 2020 - 2021*



Note: Data for Thai inflation were extracted from the National Statistical Office (NFO)
Data for Brazilian inflation were extracted from the Brazilian Institute of Geography and Statistics (IBGE)
Data are available in the appendix

Figure 3 - *F&B Accumulated Inflation 2020*

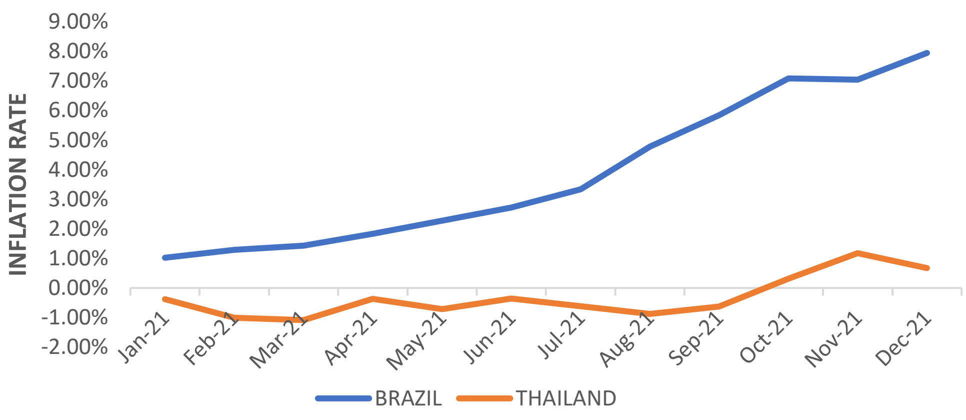


Note: Data for Thai inflation were extracted from the National Statistical Office (NFO)
Data for Brazilian inflation were extracted from the Brazilian Institute of Geography and Statistics (IBGE).
Data are available in the appendix

Although Thailand had a good performance in F&B exports during the first quarter of 2020 (Q.1/2020), as well as in the previous quarter, Thailand suffered from an arduous drought that impaired the crops. According to NESDEC (2020), agricultural production contracted significantly. One of the main hampered products is paddy (-29.4%), maize (-29.2%), sugarcane (-12.7%), and palm oil (-8.3%). Then this decrease in the Agricultural Product Index (API) was followed by a rise in the Agricultural Price Index, which rose by 8.8%. However, those specific shocks could not push prices up due to, partly, the decline in demand; for example, the wholesale of F&B declined 6.1% for this same period. Despite this troubled period, with a pandemic and droughts, Q1/2020 F&B average inflation was only 1.8% larger than in 2019 for the same period. Unlike Brazil, Thailand had a modest rise in its slope curve during Q.3/2020, mainly due to seasoning and poultry, albeit none of these items' prices rose more than 3%. In Q.4/2020, the weather condition improved for the first time in the year, raising the agricultural supply and releasing the pressure on prices.

In Brazil, during Q.1/2020, the F&B inflation started to increase mainly because of the sub-group "food consumed in-house". Figure 02 reports that, in Q.3/2020, the curve kinked, becoming steeper, due to the acceleration in the monthly rate. According to the Institute of Applied Economic Research - IPEA (2020), after the Q.3/2020, the YoY (year over year) food inflation was responsible for 70% of the headline inflation, although this component has no more than 23% of weight in that index. As stated in IPEA (2020b), rice and cereals, in general, were the villains for that acceleration. Moreover, rice and beans (the typical Brazilian dish) had a rampant rise across the year 2020, 69,5% and 40,8%, respectively (IPEA, 2021). Furthermore, when the pandemic onsets, some people changed their consumption behavior, anticipating purchases of storable food for precautions. It made the prices of that specific goods soar. A good example was the rampant canned tuna in Thailand during the Q.1/2020.

Figure 4 - *F&B Accumulated Inflation 2021*



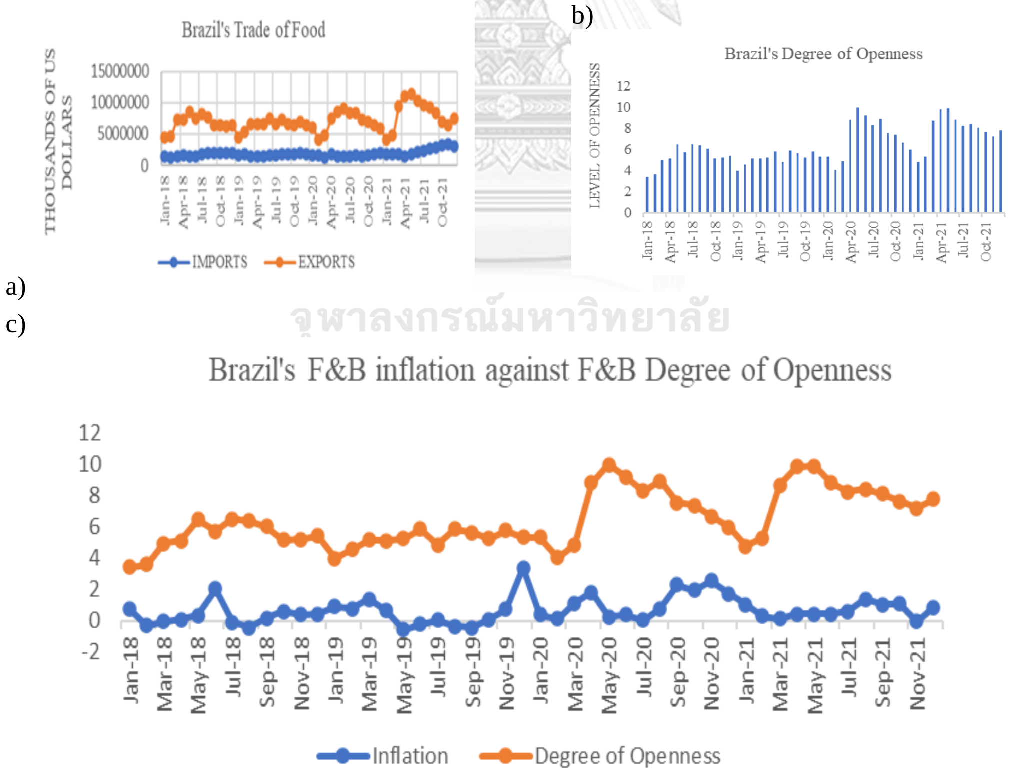
Note: Data for Thai inflation were extracted from the National Statistical Office (NFO)
Data for Brazilian inflation were extracted from the Brazilian Institute of Geography and Statistics (IBGE).
Data are available in the appendix

According to the NESDC (2021), Thailand overcame the bad weather condition in Q.1/2021. The rise in the production of rice (8.8%), fruits (7.9%), and maize (21.4) was expressive. Along with other factors, it helped keep prices below zero. Following the same trend as Thailand, Brazil saw reduced inflation rates in Q.1/2021 compared to the previous quarter. Nevertheless, compared to the same period of the previous year, the price level was higher. The production side contributed to cooling down the prices in Q.1/2021. Pork meat (17%), milk (6.6%), fruits and vegetables (between 6% and 15%) were some of the products which had price reductions (IPEA, 2021b). In Thailand, for Q.3/2021, the Agricultural Produce Index rose the figure by almost 9%, helped by the persistent good weather condition. Fruits and paddy productions had massive expansions – 37% and 12%, respectively –, along with a significant decrease in Agricultural Price Index – negative 4.5% (Nesdec, 2021c). All these numbers are in line with the negative position of the price curve in this period (figure 03). In contrast to Thailand, Brazil saw price hikes across Q.3/2021. Figure 03 shows a kinked in Brazilian's price curve. Some supply-side adversities can explain why the curve is steeper from July onwards. Meat beef and milk production growths were extremely negative throughout Q.3 and Q.4/2021. Furthermore, grains (except soy and wheat) and vegetables had negative performances (Ipea, 2021c and Ipea, 2021d). Thailand, in turn, was hit by the adverse shock in animal protein (shrimp and pork) by the end of Q.4/2021 (Nesdec, 2021d), which could not cause a significant impact on inflation for that year.

Another element that the literature points out as an inflation driver is the degree of openness. According to Romer’s Hypothesis, there is a strong and negative correlation between the degree of openness and inflation, mainly when the economy is politically unstable and has a less independent central bank (Romer, 1993). From the publication of that seminal article until today, many scholars tried to test whether this relationship holds up in different scenarios. For instance, in evaluating this relationship for food inflation in Kenya, LIN AND WANG (2017) did not find any relationship between trade openness and food inflation in the short run. Nevertheless, in the long run, this study supports Romer's hypothesis that an increase in trade openness has a reducing influence on inflation. On the other hand, ECLAC (2008) states that food exporters that increasingly sell into international markets have experienced accelerated food price inflation.

FLACHSBATH & GARRIDO's studies (2014) confirm that deeper market integration increases global price transmission elasticities, worsening food CPI pressures during global shocks. Many authors argue that countries that are more integrated into world markets might show higher world price transmission rates. These economies would be more affected by international price fluctuations than closed ones. The Brazilian economy trades expressive volumes of agricultural commodities; however, the agricultural sector still produces even larger amounts for the domestic market. The authors' empirical tests showed that this lower degree of agricultural market integration has also led to lower food price transmission, especially in the short run (Flachsbath & Garrido, 2014, pg. 937). An opposite outcome was found in a study by MANSILLA et al. l (2020). They analyzed the connection between overall inflation and the degree of openness from January 2002 to December 2017 in Brazil. The results "suggest that efforts should be undertaken to increase Brazil's insertion in global trade since, in this scenario, the inflationary dynamic is less influenced by cyclical changes in economic activity" (Mansilla et al., 2020, pg. 1948 – 1957).

Figure 5 - *Brazil Degree of Openness*

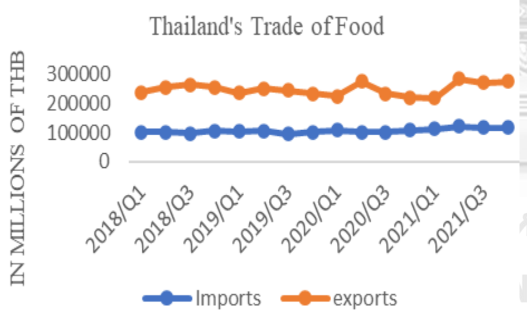


Note. 1)The degree of openness was calculated by adding the monthly food and beverage exports to imports over the monthly GDP (all values in USD). 2) The data for food was extracted from the Trademap database (ITC). 3) The data for monthly GDP was extracted from Brazilian Central Bank, time series code 4385, retrieved from: https://www3.bcb.gov.br/sgspub/consultarvalores/telaCvsSelecionarSeries.paint. 4) The list of food and beverage trade as such as all values will be shown in appendices.

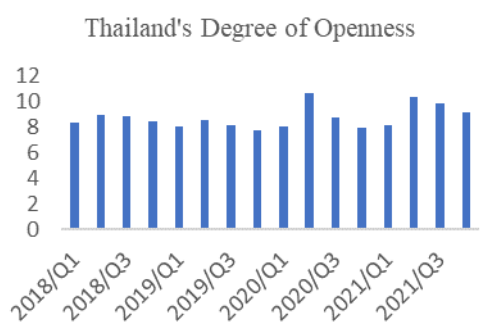
Figure 5, c reflects the inconclusive relationship between Inflation and Degree of Openness, sometimes positive, sometimes negative, and occasionally null. Nevertheless, during the two years of the pandemic, when food inflation spiked, it converged with a higher openness level.

Figure 6 - *Thailand Degree of Openness*

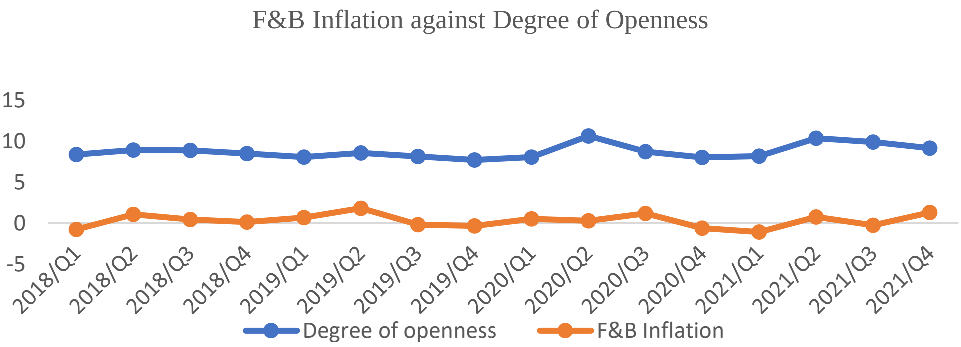
a)



b)



c)



Note 1) For Thailand, the quarterly data in THB was used because this data was not found in USD or in higher frequency. 2) The data relating to trade was extracted from the Bank of Thailand from the table: EC_XT_001: Trade Classified by Commodity Group. Retrieved date: 14 Sep 2022 23:48.3) It is not feasible to directly confront Thailand's and Brazil's Degree of Openness since the data collection was done from different sources, and the list of food trade provided by BoT might not be consistent with that offered by the Trademap.

According to HAMIDI & PRASETYO (2020), for ASEAN countries, including Thailand, Rome's hypothesis is invalid and, actually, the degree of trade openness showed a positive relationship with inflation. As can be seen by figure 6, c, for the year of 2020 and 2021, the line corresponding to the F&B inflation and that which stands for F&B degree of openness have a similar path and positive relationship, regardless of some lag.

1.2 Research Question and Objectives of the Study

1.2.1 Main Objective and Research Question

Brazil and Thailand were severely hit by COVID-19. The Brazilian economy shrunk 4.1 percent, while Thailand's GDP decreased 6.1 percent in 2020. The main objective is to investigate the causes of the discrepancy between Thailand's and Brazilian's F&B inflation behavior during the covid, considering i) the similarities between the two economies (both are developing and food exporter countries), and ii) both having been affected by the same adversity shock. Why could Thailand control F&B inflation while Brazilian inflation is high and above the target?

1.2.2 Secondary Objectives

The secondary objective of this study is to identify and evaluate the probable causes for food inflation in Brazil, the drives which make the prices soar, the weight and relevance of the variables which conduct Brazilian food costs.

An assessment will be made on whether the worldwide economic environment had the same impact on Brazilian and Thailand's food prices. The effectiveness of national price control policies will be appraised for the F&B microeconomic variable. Finally, these two countries' strategies and approaches in dealing with the rate of F&B price changes will be compared.

1.2.3 Research Question

Why could Thailand control F&B inflation while Brazilian inflation is high and above the target?

What are the drives to F&B inflation? Are they different in Brazil and Thailand?

Hypothesis:

H_0 : Domestic Energy Inflation has no impact on Food and Beverage Inflation.

H_1: Domestic Energy Inflation has an impact on Food and Beverage Inflation.

H_0 : There is no relationship between the Interest Rate and Food and Beverage Inflation.

H_1: There is a relationship between the Interest Rate and Food and Beverage Inflation.

1.3 Scope

The study will analyze the economic variables of Brazilian and Thailand that explain F&B inflation's behavior during the 24 months since the pandemic onset – January 2020 until December 2021. This timeframe is justified by the fact that it was the acute stage of the pandemic, and the vaccination programs still had not shown their full effects. Moreover, the study will appraise the dataset from periods before 2020 in case of explanatory lag variables.

1.4 Significance and Expected Benefits

"Price stability or inflation is a key macroeconomic variable that policy-makers should monitor continuously" (Gongsiang and Amatyakul, 2020, pg. 02). Understanding prices variation dynamics after the Covid-19 shock is relevant because inflation is a powerful economic indicator. The way how inflation moves leads to plenty of social impacts. There are solid theoretical and empirical data that suggest that the increase in inflation amplifies inequality. Conversely, the risk of deflation can affect the capital market severely. Moreover, businesses with debts in nominally fixed bonds experience a rise in real debt. On the other hand, financial institutions perceive a decrease in the prices of the collaterals, making their balance sheets uneven.

Another critical issue is that households with lower income spend proportionally more on foods than the people from other income ranges. According to WORLD BANK (2012), "On average, sharp increases in food prices raise poverty, reduce nutrition and curtail the consumption of essential services such as education and health care" (Laborde, 2019, pg. 03). Debating the increase in the prices of F&B is especially relevant for developing countries because this item constitutes a huge ratio of the whole CPI basket. For example, regarding Brazil, the F&B ratio in IPCA represents 18.99% of the total price index; while Thailand’s F&B accounts for around 40%. However, there is empirical evidence that this ratio has been changing during Covid-19 due to the changes in consumers’ behavior. Other important facts are that i) the price-elasticity effect for families at the lowest percentile of the income distribution is high, and ii) these households already purchase less expensive options of basic need goods. Therefore, F&B high inflation for those who are on the breadline means risks of starvation.

It is worth highlighting that the literature about inflation is well developed; however, the studies about dynamics of price behavior after the Covid-19 outbreak are still incipient. Hence, previous studies about Thailand and Brazil's inflation during the pandemic are scarce. Furthermore, the apparent dissemblance between these countries might discourage studies comparing these two economies. Nevertheless, similarities between the performance in the agricultural sector and food production aroused issues about price control capacity. This lack in the literature reinforces the importance of an investigation contrasting two emerging economies' inflation outcomes, and it will contribute to the enrichment in the stock of economic knowledge.

1.5 Limitations

One of the constraints is the non-standardization for some indices in the data systems of both countries regarding inflation. The Thai inflation data, made available by the Ministry of Commerce, utilize the CPI average to calculate the quarterly and yearly accumulated inflation rates. However, for the scope of this study, the inflation rate across quarters and during the year will be computed by the compounding method to assure rigorous isonomic handling between the two treated groups. In addition, some of Thailand's information, such as subtitles for tables, are not available in English.

Another restriction consists of the relative scarcity of dependent variables in the time series - the time frame scope of two years provides only 24 observations. Nevertheless, to estimate the coefficients will be use data points from January 2018 until December 2021. Furthermore, the methodology that will be used ARDL – Autoregressive Distributed Lag is adequate to small samples: “the ARDL procedure is statistically more valid in small samples” (Battha et. al., 2020).

CHAPTER 02
HISTORICAL BACKGROUND

This chapter envisages to compare inflation behavior in Thailand and Brazil after two massive external shocks: WWII and the Oil Crisis. This analysis aims to provide a historical perspective about overall inflation behaviors, patterns, and rate standards. Furthermore, it explores the way how the Brazilian and the Thai governments dealt with their respective price hikes and the level of inflation which Brazilian and Thai societies admit as tolerable. These periods were chosen due to them having affected both economies at the same time.

2.1 Post World War II

After WWII, Thailand established its independent Central Bank (hereinafter BOT), which had as its first challenge dealing with high and persistent inflation. It effectively managed to lower the rates from 76% in 1945 to 18% in the following year (NIDHIPRABHA, 1995). According to Haring & Westphal (1968), "Thailand, perhaps more than any other country, has been able to achieve rapid and substantial growth without inflation since World War II." (pg. 364)

The currency devaluation after the war is the most significant explanatory variable for Thailand's high inflation rates at the time. After the war (1945), the reserves in yen turned worthless, and the stirling reserve was blocked. With the Japanese occupation, Thailand was obligated to leave the sterling exchange pattern and adopt the yen standards: one baht to one yen. That exchange policy led to a devaluation of 35% of the exchange rate. Moreover, another factor pressuring inflation was the broadening of the monetary base. "Note circulation increased from 393 million baht at the end of 1942 to 2,100 million baht by September 30, 1945, when the war ended" (Haring & Westphal, 1995, pg. 366).

The bolstered money supply led to a fast inflation growth from 1952 to 1964. However, this expansion also reflected the recovery in the output. The money supply (currency and demand and time deposits) more than tripled during thirteen years, while income (GNP) increased by about 2.4 times. Analyzing the money supply and the output for these periods, is it possible to deduce a strong relationship between those two variables. The time series encompassing these 13 years shows a correlation coefficient of 0.985 between the log of money and the log of income; the positive sign means that they move in the same direction. Since the maximum value the index can reach is 1 or minus 1 (when they move in an oppositive direction), the value found indicates a solid relationship. (Haring & Westphal, 1995)

According to HARING & WESTPHAL (1995), three factors helped Thailand keep prices under control: i) financial aids that the country received after the war, ii) consumer preference for local goods, and iii) the fact that the exchange market and the foreign exchange transactions were under total control of the government.

By analyzing the data from 1938 until 1965, at table 05 below, it is possible to draw two essential conclusions. Firstly, the money supply grew quicker than inflation. Secondly, the response to inflation in 1947 was effective.

Table 5 - *Cost of Living and Money Supply in Thailand*

*Cost of Living and Money Supply in Thailand**

Year	Wholesale price index		Cost of living		Money supply
	38/39=100		38/39=100		(millions of baht)
1938	100		100		220
1939	116		103		270
1940	171		113		316
1941	225		131		425
1942	249		177		na
1943	314		265		na
1944	411		470		na
1945	......		902		2319
1946	......	1958=100	1070	1958=100	3088
1947	1700		1250		2993
1948	1650	79	1250....	59	3350
1949	1540	74	1200	57	3611
1950		76		59	4529
1951		82		65	5575
1952		87		73	5454
1953		81		80	6186
1954		79		80	6968
1955		93		84	7886
1956		95		90	8820
1957		95		95	9570
1958		100		100	10180
1959		94		96	10830
1960		92		95	12300
1961		100		102	13870
1962		106		106	15470
1963		99		106	17490
1964		93		105	19870
1965		96		102	22750

**Source:* Bank of Thailand and *IMF International Financial Statistics.*

Note: From: Haring, J. E., & Westphal, L. E. (1968). Financial policy in postwar Thailand: external equilIBC_BRium and domestic development. Asian Survey, 8(5), 364-377. Pg. 367.

The Brazilian Economic history has frequently been pervaded by inflationary issues. Concerns about inflation are always latent among economists, scholars, journalists, policy-makers, consumers, and the public opinion. According to VIANA (1990), there was a perception that inflation had been escalating during the period after WWII. Between 1951 and 1953, prices measured in then-capital Rio de Janeiro soared year after year, from 12,1% to 17,3% and to 20%. Part of this increase is explained by currency devaluation, which made production costs more expensive. To make matters worse from the inflationary perspective, a rise of 100% on the minimum wage was given. For PINHO (1990), in 1954 the government "intended to adopt strict anti-inflationary measures, blaming the debt monetization and the credit expansion as the main culprits for the inflation. In 1955, prices stabilized at 13.1%, but thanks to the high performance of agriculture rather than monetary policy". Scholars define the biannual of 1954/1955 as stabilization-oriented, through the restriction of aggregated demand. However, PINHO (1990) characterizes the period as an alternation between contractionist and expansionist programs.

From 1956 to 1960, as stated by ORENSTEIN & SOCHACZEWSKI (1990), "the recurring plans of stabilization, when implemented, were only attempts at reducing the pace of inflation to the tolerable level." However, the rise of inflation rates from 7% in 1957 to 24,5% in 1958 raised a red flag. As a response, the government announced the Monetary Stabilization Plan. The plan had two main points: lowering the pace of the monetary supply's expansion and wage-setting based on firms' costs and revenues. This plan was evaluated as extremely orthodox and aligned with the IMF. Besides, it had no political or institutional support for its implementation. For example, Bank of Brazil (BB), which had accumulated the function of Central Bank and commercial bank, was not aligned with the stabilization plan's objective regarding controlling the money supply. It is important to stress that the Brazilian Central Bank (Bacen) was created only in 1964. Moreover, organized worker pressure rendered the plan highly unpopular. Unions argued that workers would lose in wage purchasing power. Therefore, then-President Juscelino Kubitschek decided to forego the stabilization. "Under the structuralist vision, underdeveloped countries would only be able to industrialize by coping with some level of inflation, which should be managed, instead of seeking price control through stagnation" (Orenstein & Sochaczewski,1990, pg. 194)

In conclusion, by analyzing the post-WWII period, it becomes clear that Brazil and Thailand prioritized different aspects of stabilization. While Thailand followed an orthodox policy regarding inflation control, Brazil, on the other hand, admitted moderately high inflation, with general public complacency as long as the economy performed at a desirable level of growth.

2.2 OIL CRISIS

In Thailand, a big part of the country's history of price stability stems, among other reasons, from the conservative bureaucracy. The longest-running BOT governor in history so far, Dr. Puey Ungphakorn, stated that monetary growth could not exceed 2 or 3 % of the GNP growth; otherwise, it could cause high inflation, which leads to high inequality in wealth distribution.

Conversely, in Brazil, during the years that precede the crisis, 1967-1973, the level of inflation was in the range of 20 to 30%. This inflation, however, did not accelerate further due to prices and wages control. The Brazilian government created the Interministerial Board of Prices (CIP – Portuguese abbreviation) to control prices. The CPI was in charge of analyzing and allowing the firms' prices increases. (Lago, 1990). On the other hand, "the salary constraints were aligned with the inflation-fighting moods, favoring capital accumulation through a high level of profits" (Lago, 1990, pg. 287). Despite these constraints, some drivers pushed prices up. The industry installed capacity had reached its limit, making price control innocuous. This theory is corroborated by LIMA (1977, pg. 32), which states that: "the argument of 'imported inflation' is not enough to explain the acceleration of prices during

70's". The economy was about to reach the potential level of output. By 1973, it had achieved around 90% of total capacity.

Not unlike Brazil during the '70s until the '90s, Thailand also experienced pressure on its level of prices in the same period. The first impact, in 1972-1973, was a positive shock due to the appreciation of commodities. The second one was the first oil shock, in 1973-74, but its effects lasted until the end of the decade. During the second oil shock, in 1979-80, the barrel price skyrocketed, as well as general interest rates (Warr, 1996).

In the period between 1975 and 1990, import prices normally surpassed export prices, mostly due to the rising oil prices. However, nonpetroleum imported products had their role. "Since nonpetroleum imports account for more than 80% of Thailand's import bill, these nonpetroleum price increases contributed significantly to the inflation that Thailand experienced in these two periods, along with most of the rest of the world." (Warr, 1996, pg. 105). Conversely, in Brazil, "after the first oil shock, the higher prices of oil products meant only 33% of the increment on the imports bill." (Lima, 1977, pg. 30).

The effects of those two oil shocks on Thailand's balance of payments were equivalent to a deficit of 4% of GDP in 1973 and 2.4% of GDP in 1979. Both shocks, in 1973 and 1979, pushed down the growth trend by around 2%. The first shock led to an inflation of 25% in 1974 and 15% in 1979. Nevertheless, between the two shocks, the economy could perform between 2 and 7% above the trend, with moderate inflation (Warr, 1996, pg. 122). After the second shock, inflation receded, but growth remained below the trend until 1982.

By comparison, the Brazilian government forwent equilibrium at the balance of payments for the sake of growth at 10% during the period of 1975 to 1979. This period was known as "growth in a forced march." This policy was endorsed by the population, in general, because "there was a tradition of coexistence with a significative inflation rate, facilitated by a comprehensive indexation system. Regardless, there was no social security system capable of coping with the impact of a constractionist adjustment". (Marques,1991, pg. 47)

As reported by NIDHIPRABHA (1995), the relationship between inflation and growth rate in Thailand between 1971 and 1990 can be categorized into four groups, as indicated in figure 5. It is important to stress that unemployment rates were analyzed using growth rates as a proxy. If the normalized growth index (GZ) were positive (negative), it meant that unemployment was below (above) the natural rate of unemployment. With regards to inflation (FZ), a negative index number means it is below the average and, if positive, above the average for that time series. The first group (growth and positive inflation) were the years of 1973, 1977, 1978; the second group, with negative growth and positive inflation, were the years of 1974, 1979, 1980, 1981 (external shocks); the third, with both negative inflation and growth, 1971, 1972, 1975, 1982, 1984, 1985, 1986; and the fourth, with positive growth and negative inflation, 1976, 1983, 1987, 1988, 1989, 1990. It is possible to see from the table below that none of the indexes lie far from 3 standard deviations from the mean. The most extreme value corresponds to 25% of inflation in 1974.

Figure 7 - *Relationship between Inflation and Growth*

Year	GZ	FZ
1973	0.943	1.380
1977	0.957	0.088
1978	1.142	0.150
1974	-0.997	2.689
1979	-0.652	0.467
1980	-0.841	2.020
1981	-0.288	0.905
1971	-0.778	-1.107
1972	-1.099	-0.380
1975	-0.819	-0.292
1982	-1.102	-0.295
1984	-0.007	-1.075
1985	-1.302	-0.787
1986	-0.794	-0.902
1976	0.777	-0.511
1983	0.036	-0.561
1987	0.809	-0.770
1988	2.080	-0.548
1989	1.741	-1.287
1990	0.194	-0.184

Note: adapted from Nidhiprabha, B. (1995). Inflation and Macroeconomic Management in Thailand. Macroeconomic Management in Southeast Asian's Transitional Economies. Pg. 144

Regarding fiscal stance, there is a negative relationship between fiscal impulse (budgetary debt is used as a proxy) and inflation. High inflation can cause a rise in unplanned revenues as well as expenditures, but its impact on revenues is stronger, and it leads to a decline in actual deficit. However, Warr (1996) argues that the two oil shocks came along with an economic slowdown; therefore, the tax revenue does not increase sufficiently to reduce the fiscal impulse (here understood as debt), weakening the negative correlation between these two variables. In contrast with WARR (1996), NIDHIPRABHA (1995) stresses that "during the expansionary period, the fiscal deficit was reduced, and even in periods where booming is along with inflation, the so-called Tanzi effect was not observed in Thailand because there is no significative lag in tax collection" (pg.135). During both positive and negative shocks, government revenue increased. The inflation caused by these two shocks made the tax revenue expand from 28 % in 1973 to 48% in 1979. The government used this surplus to reduce indirect tax and lessen the consumer and producer prices pressure.

Still regarding fiscal stance, according to NIDHIPRABHA (1995), wages play an important role in inflation control. In the later '70s and early '80s, the Thai government tried to control inflation expectations by controlling the raises in wages. Although the minimum wage had an annual nominal adjustment, the civil servant salary raise was kept under-inflation on average. This influenced how the wages in the private sector were set. In agreement with NIDHIPRABHA (1995), WARR (1995) acknowledges that the freeze in civil servant salaries from 1982 to 1988 was important to control expectations. However, to the latter, the stabilizing role of expenditure can be seen through the lens of public investment, since it is harder to cut current expenditures (government consumption) than capital expenditures. The very rigid budgetary rule does not allow for the execution of that expenditure when the price is higher than what was defined by the fiscal law. Thus, when inflation scales and the price of capital goods rises, that expenditure is not made at all for that specific fiscal year, which contributes to deficit reduction. Nonetheless, given that public and private capital expenditures (investment) are mostly negatively correlated, growth wasn't jeopardized.

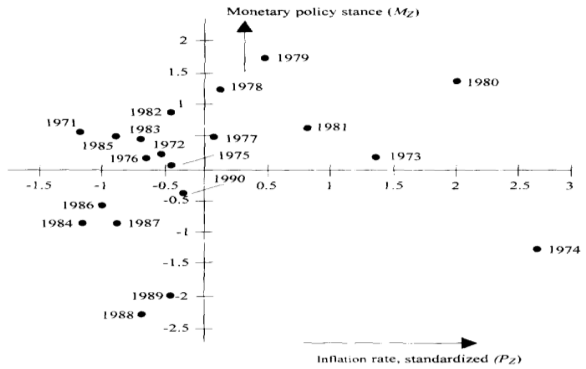
With respect to the Brazilian budget during the '70s, controlling it was challenging due to the coexistence of three different budgetary systems: the union budget, the monetary budget, and the state-owned enterprise budget. From the revenue perspective, net taxes (direct and indirect taxes minus transfers, payments and subsidies) shrunk from 15,6% of GDP in 1970 to 9,8 % in 1983.

It is consensual among scholars that large public debt can lead to high inflation. Since the beginning of the '80s, Thailand has reduced its public debt and, since the early '70s, shifted the borrowing pattern towards less inflationary means. "In the period of 1970-74, borrowing from the Bank of Thailand was 78% of total net domestic borrows. It fell to only 25% during 1986-88." (Nidhiprabha, 1995, pg. 165). In comparison, the Brazilian economy was characterized by a high debt, which, until 1964, was financed entirely by seigniorage. Until the '60s, the Open Market Operation system wasn't well developed. There wasn't any hedging mechanism against inflation, which made the OMO not attractive (CERQUEIRA, 2007). The two oil shocks worsened Brazilian debt. In 1973, Brazil had a net foreign debt of US$ 6 billion — which corresponded to one year of exports. In 1979, that figure had enlarged sixfold. (Munhoz, 1997, pg. 79).

Regarding monetary stance, Thai monetary policy had two main conflicting objectives: price and income stabilization. If inflation is within moderate standards, below 6% a year, the monetary stance will seek income stabilization. Figure 6 displays, in the x-axis, the standardized value of inflation for the period that encompasses the '70s and the '80s; and, in the y-axis, the changes in credit as a proxy for the monetary stance. When inflation was below the mean (east side), BOT acted both pro and countercyclical. In the period of 1978/1979/1980, inflation control was put aside. These years were marked by BOT weakening due to political issues. Then, even with the inflation higher than average, growth stability was prioritized, and there was no contractionary monetary policy.

Figure 8 - *Relationship between Inflation and Credit*

Figure 8.13. Monetary Policy Stance and Inflation, 1971–90



Note: From Warr, P. G., & Nidhiprabha, B. (1996). Thailand's macroeconomic miracle: Stable adjustment and sustained growth.

"The monetary contractions of 1973-74, 1979-80, and 1980-82 are cases in point. These contractions were not especially prolonged because inflation responded quickly. It must be emphasized that the past record of Thailand's conservative monetary management has been such that its monetary policy remains highly credible. When the Bank of Thailand starts raising its lending rate, inflationary expectations start to abate." (WARR, 1990, 247)

With respect to the Brazilian monetary stance, both Marques (1991) and Lima (1977) understand that the monetary policy was pro-cyclical in 1973. Nevertheless, for Lima (1977, pg. 34), the rise in money supply was a consequence of the inflationary process underway, and not its cause. It was needed to fulfill transactions in an ongoing process of prices upheaval. In 1975, 1977, and 1981, there was a monetary contraction thanks to the public debt behavior, which showed a slight decline. However, in 1977, 1979, 1982, and 1983, massive redemptions of securities pressured the monetary base upwards. Moreover, another monetary variable that explains the inflation trajectory between 1973 to 1979 was the rise of real liquidity fostered by the highly subsidized credit expansion (Marques, 1991).

In conclusion, Thailand, from 1979 to 1990, has been very conservative in deficit; the planned expenditures can never surpass 25% of the revenues. This ceiling lasted until around 1994. And, since 1960, there has been a ceiling in the debt service in the ratio of 5 percent. Debt control helped keep inflation under a tolerable level. According to Nidhiprabha (1995), fiscal discipline also helped offset the surplus caused by capital inflows from 1982 to 1995. It was crucial to hold the excess of liquidity to warrant price stability, in accordance with the quantitative theory of money.

In contrast, from 1964 until 1994, all plans of controlling Brazilian inflation were frustrated. "Between 1970 and 1973, inflation was at 17.5% on average, a modest rate from a historical perspective. However, due to demand pressure caused by deficit, inflation got into an accelerated pace from 1974 onwards. (Cerqueira, 2007, pg. 85). Since then, indexation based on past inflation was used more often, causing inflation to spill out of control at an accelerated pace. Thus, the inflation inertia component had been fed by indexation. Therefore, inflation expectations were adaptive instead of rational, at least until 1986. After 1986, policy-makers started to implement a sequence of plans which consisted of supply shocks and price freezes. These plans were known as heterodox plans of stabilization. With each shock, inflation fell sharply, but in the subsequent month, it accelerated with more intensity (Cerqueira, 2007). This heterodox policy led the Brazilian economy to hit never seen before levels of inflation, reaching almost 1800 % (YoY) in 1989. Effective stabilization only came in 1994 with "Plano Real”.

CHAPTER 3

LITERATURE REVIEW

The literature about food inflation during the acute phase of the Covid-19 Pandemic is scarce due to this theme being recent in terms of history and scientific production. With respect to Thailand and Brazil, there is no publication comparing food inflation in both countries, until the present moment. This lack of studies motivated this work to look into the reasons that drove Brazil's and Thailand's food inflation in certain ways. Having said that, this chapter is an effort to review the specialized literature and provide elements to help fill the literature void and answer this dissertation's primary concern. Due to this study's contemporaneous object, scientific articles have not been published yet. Assessing general inflation drives, overall food inflation components, specific elements of Brazilian and Thai inflation, as well as inflation and food inflation in the developing economies can furnish tools to analyze the core question of the present work. Therefore, the present literature review will explore the issues surrounding the topic question targeted by this work.

In face of the reasons above, this literature review will be organized into two main parts: i) inflation in developed countries and ii) inflation in low-income economies and emerging countries, which encompass Brazil end Thailand.

3.1 Inflation in Developed Countries

Few journal articles can be found regarding food inflation in developed economies since food does not have a relevant proportion in the consumption basket for those countries. Nevertheless, the disruption in the supply chain caused by the Pandemic raised concerns about food security and inflation. The impact of social-distancing measures on prices, such as the stay-at-home policy, was unknown since western countries have not experienced these measures since World War II. The work of AKTER (2020), even incipient, sheds light on the likely problems in terms of price changes and distortion in relative prices. The scholar evaluated the impact of related stay-at-home restrictions on food prices in 31 European countries. The indices used were the European Union's Harmonized Index of Consumer Prices (HICP) and Stay-at-Home Restriction Index (SHRI), both organized in panel data. The author created a dummy variable for the SHRI – called SHRID. That variable has a value of 0 when SHRI is equal to or greater than 1.9 and 1 otherwise. Another dummy called Post was created, in which January and February have the value of 0. For its turn, Xit is a vector of 5 different variants. The time series is from January 2019 until May 2020.

AKTER (2021) used the Differences-in-Differences fixed effed to design the model below.

$$HICP_{it} = \beta_0 + \beta_1 SHRID_i + \beta_2 POST_t + \beta_3 SHRID_i * POST_t + \beta_4 X_{it} + \varepsilon_{it}$$

eq.01

According to the model created by AKTER (2020), in equation 01, β_2 captures the trend as the shock would not have happened; therefore, the average impact of covid among the countries. The β_3 deserves special attention. This regressor captures the change in HICP during the post-restriction months and between countries and the differences between high and low restriction countries. Distinct outcomes suggested that food prices rose in countries with high restrictions, while the food prices declined in countries with fewer restrictions. However, prices stabilized for the countries with high restrictions afterwards.

After running a regression for each group of food, the results showed different outcomes for the restriction analyses. For example, for the bread, oil, and fat group, the covid impact did not show any statistical significance; nevertheless, there was statistical significance in all three months of post-shock for the animal protein.

Analyzing β_3 for all groups simultaneously, the conclusion is that the countries with high restrictions had around 1 percent further change in CPI. However, it should be emphasized that there is no statistical difference between countries with high and low restrictions from May onwards. The outcomes suggest that the restrictions could have caused price pressure when it was introduced, but there is no evidence that this pressure was sustained. This is because the supply sector might have rearranged itself to adapt to the new rules.

On the other hand, for general inflation, HA et al. (2021) identified a reduction of around 0.6% on average, considering the developed economies. The food price spike was offset by the oil price slump for the first four months of 2020. HA et al. (2021) analyzed the monthly inflation in 31 advanced and 50 emerging and developing economies from 2001 to 2021 and concluded that after the Covid-19 outbreak, global disinflation was the most short-lived inflation downturn aftershock considering the last 50 years.

Regarding the United States economic environment, the study of KWON & KOO (2009) aims to address the dynamics of food price setting. The authors intend to analyze the transmission mechanism by the stage of process (SOP) framework. They collected data from January 1985 to July 2008 from The US PPI (Producer Price Index) of crude foodstuff, feedstuffs, intermediary food, and CPI food at home. The sample was divided into the period I (1985 - 2001) and period II (2002 – 2008). For period I, the results showed the coexistence of both: cost-push and demand-pull mechanisms. However, for the second period, all mechanisms of demand-pull have not revealed any significance; conversely, the cost-push channel showed strong relevance.

The authors highlight the importance of the cost-push mechanism in price stabilization. KWON & KOO (2009) claim that the literature frequently exploits the weight of commodity prices in food inflation hikes, neglecting how the retail sector magnifies price pressures. Although several scholars infer the unidirectional price transmission mechanism, another group of researchers argue that the rise in food prices derives from the demand towards wholesale's prices. Based on these finds, it is possible to conclude that retail prices have the capability of pulling agricultural prices, establishing a dynamic relationship. Regarding exchange rate, there is no relationship between that variable and food prices in the first period, contrarily to what happened during the second period. (Kwon & Koo, 2009).

3.2 Inflation and Food Inflation in Low-Income and Developing Countries

In contrast to advanced economies, food inflation is a central concern in developing economies. Even when these economies are net exporters of food and self-sufficient, the price instability of commodities can generate losses in social welfare, food insecurity, and, ultimately, spill out to the rest of the economy, such as the nonfood sector and labor market.

According to HA et al. (2021), the last period of high inflation was registered during the 90s and 80s for low-income and developing economies, respectively. On the other hand, the Covid-19 outbreak was preceded by a long period of low inflation for developed economies, emerging countries, and low-income economies. Nevertheless, the current expectation for global inflation is an increase of one percent on average, which can impair inflation targeting for developing economies. However, one year before the outbreak, for both groups of economies, inflation was stable at a low level of 3.5 percent (emerging economies) and 3.5 (low-income economies).

Regarding low-income countries, AGYEI et al. (2021) evaluated whether the Covid-19 outbreak impacted food prices in SSA – Sub-Saharan Africa countries. The authors used the GMM (General Methods of Moments) methodology, with Panel Data, from March to September of 2020, only six months total. The product of this study was aggregated into two main models. In the first model, the Maize price was the dependent variable; the explanatory variables were: lnCovid (number of infections), lnEXRave (average exchange rate), lnInfod (food inflation), LnCopave (crude oil price), and InMaizepx$_{it-1}$ (one-month lag of the dependent variable). The second model, by its turn, used the same variables group, except for using a lockdown dummy rather than the number of inflections.

It is essential to highlight that the number of Sub-Saharan countries is larger than the number of time observations needed to apply techniques that treat endogeneity. Furthermore, the same models were used for Sorghum, imported rice, and local rice but with different combinations of countries. The authors tested all independent variables for multicollinearity and used the benchmark of 0.7 as the cut-off point. Collinearity is the level of correlation between the independent variables, and when it happens, the estimated regressor loses its reliability.

The maize price during those months was, on average, US$ 0.43 per Kg and had a standard deviation of US$0.26, which suggested a large difference among countries. After regressing the variables, they identified that the most potent regressor was the lag-dependent variable for the three food staples. 'This suggests that managing current food prices informs their future levels" (Agyei et al., 2021, pg. 108). Also, there is a positive and significant relationship between the price of these staples and the number of covid new cases. The author explains this relationship due to the rise in production costs by reducing labor supply.

To be more specific, in the first model, which used the number of infections, AGYEI et al. (2021), found two different outcomes for the exchange rate. The interaction between local food prices and the exchange rate depicted a significant negative relationship; when the exchange rate rises, food becomes cheaper, which is intuitive. However, an unexpected positive relationship between imported rice price and the exchange rate was observed. It is logical that when there is a currency appreciation, imported goods become cheaper compared to domestic goods. However, with the currency appreciation, the demand for imported rice has increased; therefore, the price elasticity of demand pulled its price up.

AGYEI's et al. (2021) article concludes that the number of infections interferes with food price changes. However, in line with AKTER's (2021) studies (which did not find the relationship between lockdown and food prices from May of 2020 onwards), AGYEI' et al. (2021) did not find any association between lockdown and starchy food staples, excepting maize. The maize behavior can be explained by the fact that this staple was a cheaper product compared to sorghum and rice. Therefore, being an inferior good, when income decreases, maize consumption increases, putting pressure onto its future prices.

As AGYEI's et al. (2021), ADEWOPO (2021) specifically evaluated price changes over 11 weeks during the first Covid-related lockdown in Northern Nigeria, focusing on the lockdown effect. In order to do this in real-time, the author used a digital crowdsourcing tool. The proliferation of mobile phones and internet access, along with citizen participation, has the potential to provide real-time monitoring of food prices. The benefit of this method is that it allows official instances to issue rapid and context-specific intervention. Furthermore, this method can spot inconsistencies in official ones. "Crowdsourced price, averaged on weekly basis, was slightly higher than the prices reported by the National Bureau of Statistics" (ADEWOPO, 2021, pg. 5). Seven hundred volunteers collected food price data of some staple foods daily. This tool was part of a broader program called Food Price Crowdsourcing in Africa (FPCA), allowing data collection before Covid, during the lockdown, and during the lockdown easing.

Unlike AGYEI et al. (2021), ADEWOPO (2021) identified a persistent rise in grain prices after the lockdown. The daily price data, on average, consistently showed higher grain prices in 2020 compared to the preceding year. Retail prices of maize and rice were, on average, 26% and 44% higher. The maize price after lockdown easing continued to rise sharply, likely due to the limits imposed by the importation policy. Likewise, rice prices continued to increase despite the lockdown easing.

According to ADEWOPO (2021), prices did not return to the pre-covid level, resulting in many households experiencing food insecurity. Distinctly from what AKTER (2021) concluded for European countries, in Northern Nigeria, the lockdown, by itself, caused persistent food inflation according to the first scholar. One interesting factor for these different outcomes can be partially explained by the changes in the logistics of doing the groceries. Data show that the mean distance traveled for shopping was reduced by 54%. Restrictions in mobility may have reduced the consumer's bargaining power. After the lockdown, along with the rise in the distance traveled to shopping, the size of the packages had increased, and probably consumers were attempting to catch up on postponed purchases. This can explain, in part, the reason why food inflation continued to grow after the lockdown restrictions.

For developing economies, the monetary stance has a prominent role. However, there is no consensus about which of the negative or positive impacts will have more weight. For example, there is no common understanding if monetary policy stabilizes food prices by reducing the aggregated demand. Many scholars advocate subsidies as the best way to stabilize food prices and consumption because it leads to a lower output loss compared to a rise in the real interest rate. BHATTACHARYA & JAIN (2020) investigated the effectiveness of this channel in the presence of elements that impact the supply side by increasing production costs and working capital.

Furthermore, those scholars argue that a tightening in monetary policy by raising the cost of capital impacts total food production cost no matter if the food sector is capital intensive or not. When the food sector is capital intensive, it is easy to understand the connections. In this case, a rise in interest rates increases the opportunity cost of capital and worsens financing conditions. On the other hand, when the food sector is not capital intensive, it is affected by the monetary tightening due to the capital-intensive nonfood sector increasing the ratio of labor/capital; then, with the rise in demand for labor, wages also rise, affecting the food sector through demand, even when it is not capital intensive. The author emphasizes that the monetary tightening must be stubborn to show any effect in reducing food prices. "By the side of the demand, aggregated demand channel can outweigh production cost channel via sustained monetary contraction." (Bhattacharya & Jain, 2020, pg. 123)

The effectiveness of interest rate hikes in food price stabilization is far from being an uncontested theme. FRANKEL (2008), cited by BHATTACHARYA & JAIN (2020), found that real interest rate lowers aggregated real commodity price, including agricultural commodities. Nevertheless, Hammoudeh et al. (2015), using the VAR model from US quartering data from 1957 to 2018, found that, "lowering a monetary tightening, food prices persistently rise after an initial decline" (Bhattacharya & Jain, 2020, pg. 126). These two studies are examples of how the specific literature can diverge concerning this point.

Furthermore, the study conducted by BHATTACHARYA & JAIN (2020), with panel data and quarterly data (from 2006 to 2016), compared food inflation dynamics in developed countries (US, UK, Canada, Japan, Italy, France, and

Germany) against emerging economies (Brazil, Russia, India, and China, South Korea, Chile, Mexico, Turkey, and Hungary). The authors spotted different aspects of the monetary policy on food price stabilization. For the emerging economies group, a 0.1% increase in the interest rate causes, on average, food inflation to increase by 0.01% immediately, but this change is transitory. "This study stands with the existing literature, which asserts that the relationship between monetary stance and food inflation is weak in emerging economies due to its underdeveloped financial system, low level of financial integration" (Bhattacharya & Jain, 2020, pg. 131). Additionally, the negative effect of the interest rate related to aggregated demand is more than outweighed by the increase in production cost.

These authors applied the FEVD (Forecast Error Variance Decomposition) methodology. The outcome indicated the following main contributions to the food inflation variation: income growth, exchange rate, real consumption, investment growth, and headline inflation. All these elements were used with a lag of 4 quarters. For emerging economies, variation in GDP growth can explain only 7.77% of the variation in food inflation. However, the main takeaway from this work is that the policy rate has a positive and significant effect on food inflation; in other words, when the interest rate rises, the overall result, after some quarters, is an increase in the variation of food prices. "A monetary tightening may turn out to be destabilizing" (Bhattacharya & Jain, 2020, pg. 133)

Many scholars also observe a close and vital relationship between food inflation and monetary stance through the exchange rate channel. For instance, in emerging economies, according to HA et al. (2020), ten percent in exchange rate depreciation has been estimated to raise inflation by about one percent. These authors claim that food price increases are highly correlated to currency depreciation because of the cost of importing food products. This outcome is in keeping with AGYEI's et al. (2021) findings for low-income countries. However, differently from AGYEI et al. (2021), HA's et al. (2020) studies analyzed developing economies during the outbreak of Covid-19.

The demand depression was the main player in the price downturn in the first quarter of 2020. Besides, from the second quarter of 2020 onwards, the change in disinflationary pressures also derived from the recovery in the crude oil price and demand uprises, each one of them contributing, on average, with one and two-thirds, respectively (Ha et al., 2020).

In agreement with HA et al. (2020), BHATTARYA & JAIN (2020) spotted the link between food commodity prices and monetary policy. We shall suppose a tightening in monetary policy, which entails an interest rate increase. One of the first impacts of a contractionist policy is a sudden boost in storage costs. Given that, the firms have an economic incentive to release their inventories, temporarily shifting the supply curve. However, once the interest rates remain at a high level, so does the inventory carrying costs, which discourage firms from maintaining a high stock. Secondly, bonds become more attractive than holding commodity assets, which can decompress demand for this commodity, which in turn might negatively impact retail prices. Third, the aggregate demand falls because investment is negatively correlated to the interest rate. "The two latest movements release the pressure on inflation food, while the first one pulls the prices up." (Iddrisu, 2021, pg.57). Although the reduction in aggregate demand has less impact on food inflation than on nonfood inflation, the optimal level of monetary stance promotes food price stabilization.

The current literature has been considering that the correlation between the interest rate on food prices is rising. AKAN's (2009) and HAMMOUCH et al. (2015) (as cited in Iddrisu, 2021) research concluded that when interest rates rise, so do food prices. In both studies, the outcomes suggested a positive and persistent relationship between food inflation and interest rate.

To reckon how and by how much food inflation is affected by monetary decisions, IDDRISU (2021) analyzed the monthly time series from January 2006 to May 2018 in ten different developing countries. The variables used were: MPR (Monetary Policy Rate), FOOD (Food Inflation), Real Gross Domestic Product (RGDP), HCE (Household Consumption Expenditure), GFCF (Gross Fixed Capital Formation), USD (Exchange Rate domestic against the Dollar), and GFPI (Global food prices index). The author applies wavelet-based quantile regression. This methodology's advantage is preventing outliers that mislead the forecasting accuracy and spots asymmetry in the relationship between monetary policy and food prices.

Another advantage of the Wavelet approach is its ability to handle non-stationary data. First, IDDRISU (2021) used wavelets to decompose the time series into high and low frequencies. The father wavelets are integrated to 1 and can capture the trend and the time series' smooth part (low frequency). The mother is integrated to zero and captures high frequency. Second, after decomposing the series, the author applies quantile regression techniques to assess whether monetary policy affects food inflation in different quantiles and horizons. The quantile of interest was 25th, 50th, and 75th.

In this vein, the author estimates the variable of interest by means of two different models. The first employs the Real Gross Domestic Product, Exchange Rate, and Global Food Price as controlling vectors. On the other hand, the second model applies the controlling vector to Real Household Consumption Expenditure and Real Gross Fixed Capital Formation. (Iddrisu, 2021)

The core of IDDRISU's (2021) arguments is that correlation between monetary policy and food inflation relies on the following cause-consequences chain: the agriculture and food processing sectors are capital intensive and highly automatized nowadays; therefore, interest rates directly affect their production costs. Additionally, given the inelasticity of food demand, production costs are easily passed through to consumers. "Moreover, and on account of the same reasoning, food item from the food sector get to final consumers through the efforts of wholesalers and retailers who also invest heavily on transportation infrastructure, warehouse, packing and packaging equipment." (Iddrisu, 2021, pg. 69). Monitoring food price stability is crucial due to its influence on overall prices. When total inflation increases, the monetary authority tightens the monetary stance, which, in turn, pressures the food price by rising production costs.

From the lessons of IDDRISU (2021), a contractionist monetary policy by raising production costs can end up being a factor of instability for food inflation. To warrant food price stability, especially in developing and low-income countries, it is critical to utilize fiscal policy (such as subsidies). The reflections of KAUR (2020) partially corroborate those of IDDRISU (2021). The former author emphasizes that a monetary tightening makes capital more costly, then the production sector shifts and becomes more labor intensive, causing wage and price pressures. For the demand side, a rise in the interest rate causes consumption and investment to diminish, therefore lowering general prices, including food. It is essential to highlight that KAUR' (2020) is based on the Indian economic environment and cannot be extended to other emerging economies.

However, while a strand of scholars advocates that the Central Bank must interfere no matter the causes of inflation, another group sustains the hands-off approach (Subbarao, 2011). SUBBARAO's (2011) study aims to investigate the underlying conditions that have driven Indian Food inflation to a higher level compared to the last 60 years, even in the face of record production of foodgrain. This study's goal is to figure out what has changed in the recent years. For this scope, the author set as recent years: 2008 until 2011.

SUBBARAO (2011) lists some non-monetary elements that might have contributed to the increase in Indian food inflation. First, dietary behavior includes more protein. According to Bennett's law, the higher the income, the less proportional spending on starchy staples in favor of more expensive sources of calories. Along with the increase in income, India also increased its consumption of protein-rich items. However, the supply side did not catch up with this change. Secondly, inclusive growth. Two laws warranted minimum income for rural areas. The first law was the Mahatma Gandhi National Rural Employment Guarantee Scheme which ensured at least one hundred days of wage employment to rural labor. This pushed up real wages for rural areas. The second is the Minimum Support Price Policy. Thirdly, the international environment. According to OECF-FAO's estimative, food prices would continue to spike from 2015 to 2020. This means that the international market integration would not soothe the domestic situation. Furthermore, the financialization of agricultural commodities amplified the disequilibrium between supply and demand. Although, for India, the relationship between the future market and food prices has not been empirically proved.

Regarding the pandemic context, HA et al. (2021) point out for overall inflation that Central Banks, in general, kept doing accommodative policies so as to not jeopardize growth and due to believing that inflation expectations are well anchored for the medium-term.

Using the same methodology as IDDRISU (2021), BANERJEE et al. (2020) analyzed 31 emerging and 12 advanced economies separately from 1990 onwards. The author employed quantile regression through panel data. This choice was justified since the OLS conventional regression estimates averages while quantile regression focuses on edges. The author exemplifies the cases in which financial restriction can act negatively and positively related to inflation. For conventional methodology dealing with averages, the regression could not demonstrate the relationship between those two variables. Concerning financial conditions' impact on general inflation, the studies conducted by BANERJEE et al. (2020) are aligned with IDDRISU (2021). For emerging countries, tighter financial conditions contribute as much to the downside (left tail of the distribution) as to the upside (right tail of the distribution) of inflation risks.

In emerging countries, food inflation and monetary policy have a dynamic relationship. Apart from humanitarian matters, persistent food inflation can be challenging for the monetary bodies. Some scholars advocate that central banks should look after the side effects or second-round effects caused by food inflation on core inflation. However, "there is evidence that food price inflation dynamics can differ in emerging economies. In this sense, ignoring food inflation in monetary policy actions could lead to policy mistakes" (Ribeiro, 2019, pg. 82). According to WALSH (2011), cited by Ribeiro (2019), food price instability in emerging countries tends to be more persistent and spread more easily through other sectors. Moreover, as the proportion of food on CPI is larger in developing economies compared to advanced ones, so is the pass-through to core inflation. As stated by KAUR (2020), although inflation targeting helps forging the Central Bank's credibility and the stationarity of the inflation rate, Central Banks should analyze where inflation stems from before using interest rate stances.

In a study assessing whether food inflation plays an important role in core inflation, RIBEIRO (2019) appraised Peruvian economic data before the Pandemic, from 2010 to 2016. The food sector is highly susceptible to shocks. While there is a consensus that monetary policy should not react to transitory supply shocks, there is also a consensus that Central Banks should act timely when the supply shock is significant enough to generate second-round effects on inflation. The timeframe studied was marked by elevated volatility in food prices. Nevertheless, the inflation expectation was well anchored and stable. The outcomes of Ribeiro's work suggest that the Peruvian price expectations have a forward-looking composition, which reduces the inflationary inertia and helps keep transitory shocks only temporary.

RIBEIRO's (2019) approach is in line with SUBBARAO (2011) 's observations. For the latter author, in scope of the Indian economy, a rising in food inflation is often caused by a supply shock. Therefore, Central Banks must evaluate whether the shocks are temporary or permanent. When the shock is permanent, it tends to also impact core inflation and inflation expectation; only then would the Central Bank's action be suggested.

Central banks also need to evaluate the nature of the shocks. Contrarily to demand shocks, which affect growth and inflation in the same direction, negative supply shocks cause downturns in growth and spikes in inflation. In such scenarios, Central Banks must choose between growth and price stabilization.

The spiraling of food inflation should not be the only concern of central banks. It is well known that general inflation exacerbates inequality; is food inflation more powerful in doing this? WASH et al. (2012) studied the differences between the impact of food and nonfood inflation in India. The authors argue that high food prices can hurt poor people in urban areas but, in rural areas, nonfood inflation can be more prejudicial than food inflation. High food prices can benefit small rural producers, but this only works for those who are net food producers. Additionally, food inflation in rural areas contributes to reducing inequality by encouraging the poorest producers, who cannot take advantage of food inflation, to migrate to cities; therefore, an inflationary food environment expels the poorest, softening rural inequality.

On the other hand, many scholars and researchers worldwide suggest that long-run inflationary scenarios worsen the income distribution. WALSH et al. (2021) ponder that inflation does not contribute to rural equality because poor people do not have those mechanisms available for high-income people to cope with inflation, such as pursuing financial assets with returns that offset inflation. Moreover, consumption anticipation, another mechanism of inflationary hedge, is not feasible to deal with food inflation due to its perishability.

3.2.1 Brazilian Food Inflation

The interaction between food inflation and monetary stances in Brazil's environment during the pre-pandemic period was analyzed by IDDRISU (2021), whose research was comprehensively described in the previous section. In the Brazilian case, results show statistical significance only from the 8 to 16 months horizon and just for the 25th quantile. One percent increase in the interest rate leads to an increase of 0.393 in food inflation. Over 16- and 32-months horizon, monetary policy is statistically significant for all quantiles. The marginal change in monetary policy leads to a 1.134%, 1.088%, and 1.183% change in food inflation for the 25th, 50th, and 75th quantiles, respectively.

Other non-monetary macroeconomic variables were also regressed against food inflation. For real DGP, the estimated coefficient reported a small magnitude. However, it was statistically significant for the 25th quantile in all horizons. Brazilian food inflation seems insensitive to the Global Food Price Index (GFPI), except for the horizon of 16 to 32 months, which has a positive sign and statistical significance at a 1% of the significance level. The coefficients for all quantiles in that horizon were around 0.1, which means that for each unit of variation in GFPI, food inflation in Brazil changed by around 0.1 units. In other words, for a specific range of lag – 16 to

32 months – the world food inflation led to a rise in Brazilian food inflation at an economic and statistical level of significance. (Iddrisu, 2021)

Exchange rate had the most expressive coefficient in size. This regressor showed a positive relationship and statistical significance for all quantiles for the 16 to 32 months horizon. A one percent increase in the exchange rate (here understood as the Real depreciation against the Dollar) led to an increase of 4.2%, 5.0%, and 4.2% in food inflation at the 25th, 50th, and 75th quantile, respectively. Nevertheless, an unexpected and statistically significant outcome rose in the horizon of 2 to 8 months for the 75th quantile. This regressor is negatively correlated to food inflation. For each unit of exchange rate diminished, the food inflation rises by two units. (Iddrisu, 2021). BANERJEE's et al. (2020) studies were inconsistent with the outcome of the 2 to 8 months range. "The depreciation of the Brazilian real in the first quarter has a relatively strong effect in raising upside inflation risks, as shown by a proportionately larger movement in the upper tail than in the lower tail" (Banerjee et al., 2020, pg. 05)

3.2.2 Thailand Inflation

In recent years, Thailand has not been showing signs of persistently high inflation. Bearing in mind the scarcity of journal articles about Thailand's inflation behavior after covid, it is worth investigating this key economic behavior in previous shocks, such as the 1997's crisis. SIREGAR & RAJAGURO (2005) performed an empirical analysis covering the period between 1985 to 2002 and the role of monetary aggregates in inflationary pressures. For the author, monetary aggregates play an important role in explaining price levels after the 1997's crisis. "In late 1997 and early 1998, many of these economies had experienced excessively high growths of money base due to the liquidity supports provided to troubled banks and the impact of depositor runs on banks" (Siregar & Rajaguro, 2005, pg. 869). By 2000, Thailand had adopted the inflation targeting system. They also embraced monetary growth, interest rate targeting, and management of exchange rate volatility to achieve price stability.

To assess the likely causes of general inflation after the 1997's shock, SIREGAR & RAJAGURO (2005) built a working model based on the monetary theory, which establishes that the prices variation rate is equal to the growth rate of the nominal money supply ($\%\Delta\ m^s_t$) minus the growth rate of actual money demand ($\%\ \Delta\ m^d_t /p$). Moreover, $m^d_t /p = f(Y, r, rf, ed)$, where Y is output, r is the internal interest rate, rf is the foreigner interest rate, ed is the expectation of devaluation, and $\Delta\ p_t = f(\Delta\ y_t, \Delta\ r_t, \Delta\ rf_t, \Delta\ ed_t, \Delta\ ms_t)$. The expectation was that the outcome would be positive for the expectation of depreciation, foreigner interest rate, domestic interest rate, and money supply, and negative for output.

Contrary to SIREGAR & RAJAGURO (2005), the study of GONGSIANG & AMATYAKUL (2020) took into account key variables from the real economy, such as weather conditions, oil price, and Leading Economic Index (LEI). The data used covered the period between January 2003 and June 2020 and it used monthly inflation rather than quarterly inflation so as to have more data frequency. The dependent variable was one-year- ahead in the Thailand Consumer Price Index.

SIREGAR & RAJAGURO (2005) estimated the coefficients through the Autoregressive Distributed Lag Model (ARDL) method. Four different regressions were estimated pre-crisis and post-crisis, using bilateral exchange rate and Nominal Effective Exchange Rate (NEER). The expected signs of the coefficient are consistent with the theory mentioned in the previous paragraph. All variables showed statistical significance at 10%, at least. All of those that did not meet this requirement were withdrawn. Each regression has a different combination of variables, though. Conversely, GONGSIANG& AMATYAKUL (2020) applied quantile regression methodology. For this work, the quartiles of interest are 10th, 30th, 50th, 70th, and 90th. Shall we consider 10th and 90th, respectively, left and right tail of the distribution. The use of quantile regression is helpful when we have some assumptions: i) Non-linearity of the predictor and future Inflation; ii) the regressor of the equation which predicts future inflation varies throughout the quantiles, and iii) restriction in using the Ordinary Least Square (OLS).

The model designed by SIREGAR & RAJAGURO (2005) for the post-crisis period has higher explanatory power compared to the model before the crisis. For the pre-crisis model, using the bilateral exchange rate (Baht against the US dollar), the R-squared value was 0.17; on the other hand, the model with NEER had a 0.23 R-squared. For the post-crisis model, using either bilateral exchange or NEER, both performed 0.45 of R-squared. It is understood as R-squared the percentage of variation in the dependent variable that is caused by the independent variable. "The exchange rate factor, the base money, and the domestic interest rate are found to be significant in causing price changes in both regressions of NEER and nominal baht against the US dollar. However, the foreign interest rate is significant only for the bilateral nominal exchange rate case." (Siregar & Rajaguro, 2005, pg. 877)

For the pre-crisis of the 1997 environment, the exchange rate had a smooth fluctuation, due to the regime's rigidity. For the bilateral exchange rate, the Thai baht had a slight appreciation, an average of 0.18%; on the other hand, the Thai currency had depreciated by around 0.8% considering NEER. Moreover, the role of the exchange rate variable alone corresponds to around 9 % of the variation in the inflation rate, while the growth rate of money supply and the expectation of appreciation altogether explain 10%. During the after-crisis period, the Thai government reduced monetary growth, preventing persistent inflation. From December 1997 to December 1998, the monetary base was lowered by 0.35%. "However, the weak and volatile local currencies contributed significantly more to the price fluctuations than the base money" (Siregar & Rajaguro, 2005, pg. 882).

In sum, according to SIREGAR & RAJAGURO (2005), control of the monetary base, early adoption of the inflation-target framework, and management of local currency volatility play a more relevant role in fighting against inflation, leaving the interest rate policy with secondary importance. Furthermore, the low R-squared suggested that the price rate variation had increased mainly due to its own shock.

The studies of GONGSIANG& AMATYAKUL (2020) encompassed, among others, raw food inflation and core inflation. For the latest, the relevant drivers were Inflation Expectation, Wage, LEI, World Production, NEER, Credit Spread, and World Food Price. For example, regarding NEER, the sign was negative, and the magnitude of the coefficient was growing larger along with the percentiles. Contrarily, SIREGAR & RAJAGURO (2005) found that the variable NEER showed different signs depending on the lag.

Concerning raw food inflation, the authors selected data from 2006; after the selection process, they left five variables. The explanatory variables were selected by using LASSO (Last Absolute Shrinkage and Selection Operator). After this triage, the variable sorted were: i) CBOE VIX (Volatility Index), LEI, World Food Price, Retail Oil Price, and Ocean Nino Index (ONI). No statistical significance exists for the ONI index at any of the quintiles. The retail oil price was not significant at the edges, just around the center (quantile 50th). The volatility Index was significant throughout all quintiles, and the coefficients are pretty similar to each other (0.21 and 0.22). The scholars spotted that the likely reason is that investors shift their preferences toward commodities, such as food, when the uncertainty is high. World Food Prices were statistically significant for all quintiles, and their size rose along with the quintiles, from 0.21 to 0.5. This means the higher the quantiles, the more prominent the impact of World Food Prices on Thai food inflation.

According to the data shown in chapter 1 of the present dissertation, food inflation in Thailand during 2020 and 2021 was low and stable. SEREENOCHAI & ARUNRAT (2021) described non-monetary or fiscal strategies that helped Thai people to cope with this issue during the Covid-19 Pandemic. On the countryside, some communities created strategies to deal with food insecurity, building up net support mechanisms to help each other. These strategies were outlined without a monetary element. SEREENOCHAI & ARUNRAT (2021) listed three local communities' tools developed to manage food insecurity challenges in the Covid-19 Pandemic. The first was the food bank; local community leadership encouraged households to grow their own vegetables for consumption. Some communities count on a local and informal or semi-formal institution called a paddy rice fund, where the villagers can borrow rice for a year, and the principal and interest rate are paid back with rice as well. Second, some traditional villages which had never worked together before the Covid-19 crisis started a barter system that consisted of product exchange – 'P2P" (people to people and product to product). Third, the creation of collective pantries by a private group called "small brick."

Additionally, export barriers might have soothed the food price pressures. THAMMACHOTE (2021) argues that in 2021, Thai rice exports experienced their lowest volumes in two decades due to an increase in Bath value and production costs. Moreover, processed fruits and vegetables for Q.2 and Q.3 of 2020, had extremely negative growth in exports.

3.3 General Considerations

According to HA et al. (2021), for emerging economies, the headline inflation reached a low level in May 2020 and then rose; the inflation downturn lasted for just five months after the onset of the Pandemic. By its turn, the global financial crisis (2008) had a turning point 14 months after the Lehman Brothers' bankruptcy (Ha et al., 2021). After the first quarter of 2020, the fade in demand was offset by the supply shock and supply chain disruption. For the inflationary period, HA et al. (2021) argue that the demand side once again played a highlighted role; consumers shifted their behavior, increasing online purchasing. On the supply side, there was a decompression once firms had learned how to deal with the Covid-19 situation. Nevertheless, the demand side outweighed supply enhancements.

From the perspective of HA et al. (2021), global inflation is susceptible to pressures that can pull it down or push it up, making the year 2021 an inflection point. The author gathered elements that can damper the prices rising, such as the well-anchored expectation, automation (which holds down wages), transparency in price setting, and the global value chain. Conversely, factors that could heat prices up, such as demand pressures, weaker fiscal position, and pressure for reshoring production emerged.

CHAPTER 04
METHODOLOGY

This study tries to assess whether the food inflation in Brazil and Thailand rose at a different pace after the Covid-19 outbreak, given all similarities between those two countries regarding food production. To address this question will be performed quantitative analyses, thereby descriptive and inferential statistics. Besides, qualitative methods will be applied to interpret the results based on the economic theory.

This research is based on two strategies. First, a panel analysis to spot differences in the level of food inflation between the two countries. Second, the two countries' food inflation will be evaluated through time series methods. A similar model will be constructed for Brazil and Thailand separately; then, the coefficients will direct the analyses. The choice of time series is, among others, due to its cleanness and easiness of interpreting the results.

Furthermore, the time series allows for analyzing the data although its autocorrelation characteristics. In addition, since we do not previously acknowledge the data's characteristics, time series offers a myriad of possibilities to treat nonstationary data. Besides, this method is well-developed irrespective of inspecting the existence of unit roots.

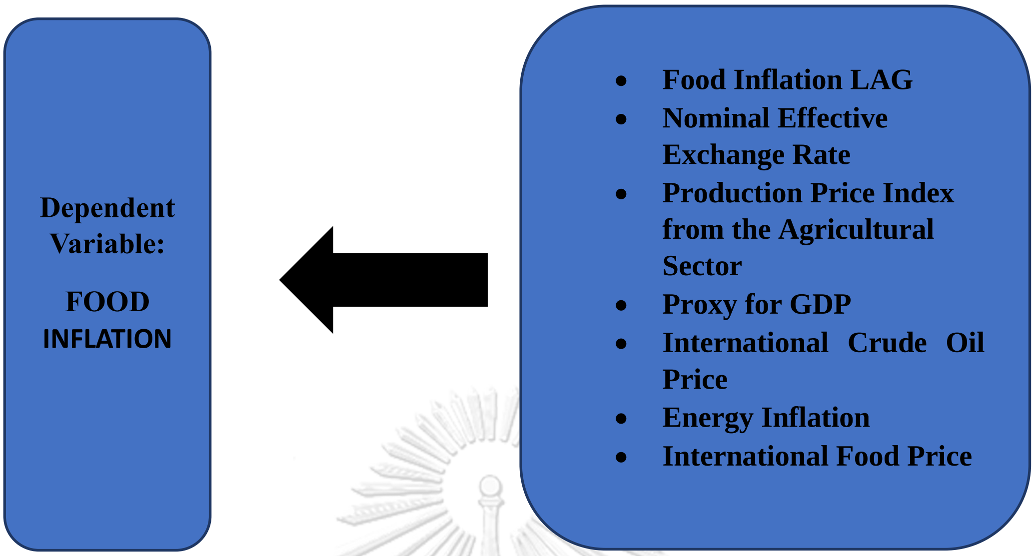
4.1 CONCEPTUAL FRAMEWORK

Findings across the literature suggested that many variables could be relevant in explaining why inflation behaves in a determined manner. The table below highlights the most common variables used to forecast inflation and assess the causality of inflation changes. Checking if this correlation remains for the two countries studied here in the cohort of 2020 and 2021 would be a pointful contribution to the literature.

Author	Dependent	Independent (drivers)	Methodology
Agyei (2021)	Maize price	• Number of infections • Lockdowns (Dummy) • Crude oil • Exchange rate • Food inflation	GMM Panel
Akter (2021)	Food price	• Controller variable vector of 5 different variables. • Stay Home restriction (Dummy)	Diff- in -diff Fix effect
Siregar, R., & Rajaguru, G. (2005).	General Inflation	• Dependent variable lag • Expectation of depreciation • Internal interest rate • Money supply • NEER • Bilateral exchange rate (US)	ARDL
Gomez et al. (2012)	Food inflation	• Tradable goods • Food inflation one lag • Nonfood inflation • Output gap	Flexible Least Square
Iddrisu & Alagidede	Food Inflation	• Monetary policy Rates • Food Inflation • Real Gross Domestic Product	Quantile Regression

Author	Dependent	Independent (drivers)	Methodology
		• Household Consumption Expenditure • Gross Fixed Capital Formation • Exchange rate • Global Food Price Index	
Gongsiang & Amatyakul (2020)	Raw Food	• Leading Economic index • Volatility index • Nino index	Quantile Regression
Banerjee et al. (2020)	General Inflation (COVID)	• NEER • Equity Return Volatility • Zero lower bound (Dummy) • Inflation targeting (dummy)	Quantile Regression Panel data
Ribeiro 2019	The gap between headline and core inflation	• Core inflation • Headline inflation • Interest rate • Currency devaluation	General EquilIBC_BRium Model
Seka et al. l (2015)	General Inflation	• GDP • PPI • REER	

4.1.1Research Design



4.2 Data

The data set was retrieved from the statistics national institutes of Thailand and Brazil, their respective central banks (BOT and Bacen), the International Monetary Fund (IMF), and the International Trade Center database. The data will primarily be time-series, encompassing Thai and Brazilian macroeconomics variables from January 2018 to December 2021. All variables are monthly frequency, and a monthly one will be used as a proxy in the case of variables that usually are quarterly, such as GDP.

The variable of interest will be Food and Beverage inflation. The independent variables (explanatory variables) will be the Food Inflation lag, Interest Rate, Currency devaluation, Nominal Effective Exchange Rate (NEER), Agricultural Sector's Producer Price Index (PPI), Proxy for GDP (Lei for Thai economic activities, and IBC-Br for Brazilian economic activities), International Crude Oil price, national's energy inflation, and international food price.

4.2.1 Descriptive Analyses

4.2.1.1 Average.

In 2020, the average monthly food of Brazilian food inflation was 1.10596%, while in the Asian country was 0.11345%, approximately. In 2021, Brazil had monthly average food inflation of 0.63848%, and Thailand had around 0.0566%. Recall that the average monthly inflation is calculated by compounding the monthly inflation of the whole year and finding the figure as if the inflation had grown at a constant rate during the entire period. The difference between the two countries seems small, but the gap grows more prominent when the numbers are calculated compounding.

4.2.1.2 – Kurtosis

The Kurtosis, in the gross definition, is the thickness of the distribution. It is essential to highlight that there are three kinds of Kurtosis. First, mesokurtic, when there is a distribution that shows no excess of kurtosis, or Kurtosis equal to 3, and this suggests a normal distribution. Second, Leptokurtic, also called tall distribution or positive kurtosis, happens when the Kurtosis is greater than 3, its pick is thinner, and the tails are thicker than they should be. A positive kurtosis leads to a high Jaquera-Bera statistic test for normality. High Kurtosis can also be a sign of an outlier or small sample. (Hill, 2011). The third one is the Platykurtic, which is a low and negative kurtosis, in other words, when the curve is flat with thin tails (Salvatore & Reagle, 2002). In this case, there is no peak; the peak is a plateau; the mean is not the highest frequency, and the values around the mean have a similar occurrence.

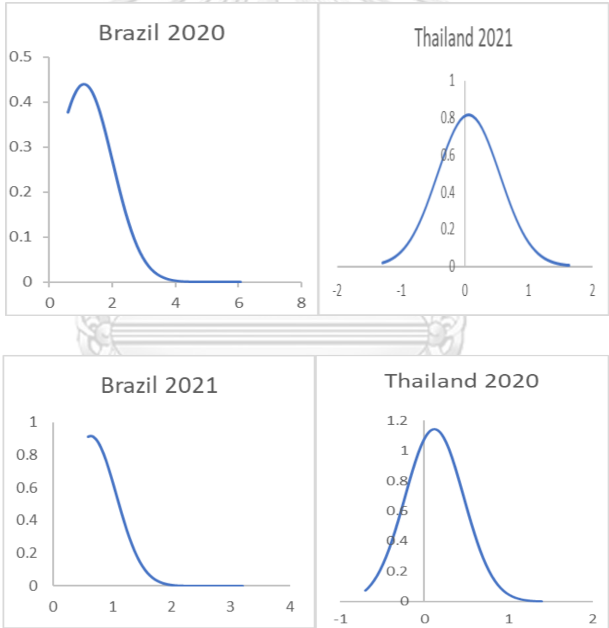
In 2020, Brazilian B&F inflation Kurtosis was around -1.65, while Thailand's was 0.41. In 2021, the Latin American country had a – 0.93 Kurtosis, and the Asian one had a – 0.75 Kurtosis. For both years, the two countries had a Platykurtic Kurtosis. It means that the frequency for the deciles around the media, for example, the 30^{th}, 40^{th}, $60^{th,}$ and $70^{th,}$ have approximately similar occurrences.

4.2.1.3 Skew

According to WOOLDRIDGE (2012), skewness defines whether the distribution is symmetric about the mean, based on the third moment of the standardized random sample. When the distribution is entirely normal, it shows skewness equal to zero. A negatively skewed distribution concentrates the observations closer to the right tail, while the positively skewed distribution gathers its observation near the left tail. For non-bell-shaped distribution, the empirical rule does not apply, which states that 68,2 % of the observations lie within +/- 1 Sd, 95.4% lie within +/- 2 Sd, and 99.6 +/- 3 Sd. Instead, it is preferable to apply the Chebyshev's Theorem (Inequality Theorem), which states that at least 75% of the observations are within +/- 2 Sd from the mean, and at least 88,89% of the observations are within +/- 3 Sd from the mean. (Keller, 2018)

Brazil's F&B inflation distribution showed a positively skewed curve, with the skewness of 0.73 and 0.19, in 2020 and 2021, respectively. At the same time, Thailand's F&B inflation distribution had a slightly positively skewed curve in 2020 (0.23) and 2021(0.53). In both cases, a possible mode is located on the left side of the median. Besides, the median is smaller than the mean. The distance between the third and second quarters is greater than the distance between the second and first quarters ($Q_3 - Q_2 > Q_2 - Q_1$). In conclusion, this indicates that might have been outliers pulling up the mean.

Figure 9 – *Brazilian and Thai skewness based on food inflation distribution.*



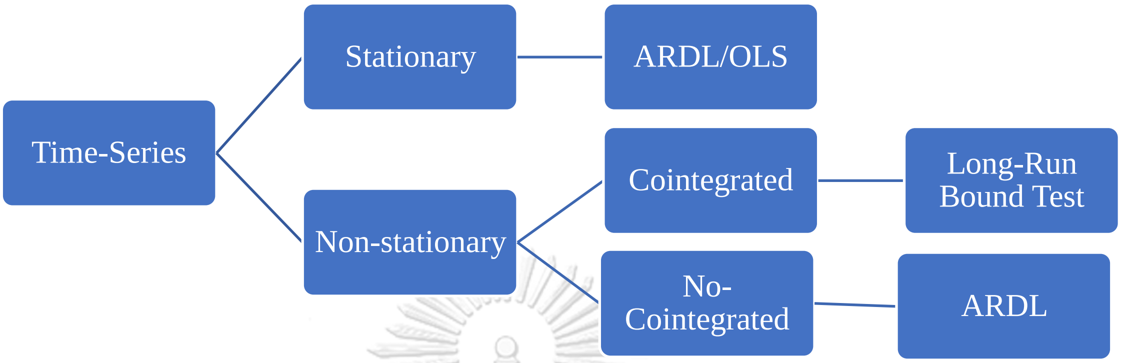
4.2.1.4 Standard Deviation and Coefficient of Variation

The Coefficient of Variation (CV) indicates the magnitude in which the data are spread. The CV is found by dividing the standard deviation by the mean. Brazil's F&B inflation CV was 2.09 and 0.68 in 2020 and 2021, while Thailand's was 3.05 and 8.32 in 2020 and 2021, respectively. It is essential to highlight that the inflation statistical mean does not converge with the financial average. Therefore, irrespective of the amplitude of the distance between the observations in Brazil's and Thailand's F&B inflation distribution, the last country shows the observations more spread than the former.

4.2.2 Inferential Analysis

Two techniques will be used. The first method will be subsidiary and consists of performing the Differences in Differences (Diff-in-Diff) Fixed Effect Panel Data. However, the heart of the present study will be assessed by means of time series analysis. The main goal is to compare and contrast how Brazil's and Thailand's F&B inflation evolve during the Covid-19 pandemic. To this end, it will be assessed whether there is a relationship between food inflation and the variables pointed out by the scholars, such as energy price, crude oil price, the international price of the food, nominal effective exchange rate, and so on.

Figure 10 - *Methodology Flow Chart*



4.3 Time-series Analysis

This section will discuss the steps to conduct the time-series analyses. The present study focuses on two individuals – Thailand and Brazil; therefore, this task can be done using two time series for each country thereby of ARDL (Autoregressive Distributed Lag) method. . Given that, a different model (equation) for each country will be run. It is important to emphasize that, although ARDL can easily accommodate panel data, tests for unit root panel data are not fully developed, such as for time series data.

Another advantage of ARDL over other existing methodologies consists of clarity and simplicity. A whole model can be summarized in a single equation, while VAR (Vector Autoregressive), for example, is a multi-equation system, with each variable demanding an individual equation. Furthermore, the ARDL is suitable for short time series and can tackle times series with different levels of integration, as long as there is no presence of variable integrated by 2 – I(2). Nevertheless, before performing the ARDL analyses, it is beneficial to scrutinize the data regarding their stationarity and unit roots.

It must be analyzed whether the time-series variable is stationary (Integration equals zero and mean, and standard deviation constant) or nonstationary (containing unit roots and the mean and standard deviation vary along with the time) should be analyzed. If nonstationary, we can use integration to transform them. The main difference between cross-section and time-series data is that the last one has a high probability that each observation is autocorrelated.

One important characteristic of time series is that each observation contains relevant information with a dynamic nature relationship. Furthermore, a dependent variable can be a function of current and past variables. Therefore, it means that a contemporary explanatory variable impacts the dependent variable now and in the future. This dynamic is known as a distributed lag model. (Hill et al., 2011)

Another characteristic of time-series data is that the past dependent variable can work as explanatory variables, mathematically expressed as $Y_t = f(Y_{t-1}, X_t)$. This variable is called lagged dependent variable. This method can be trustworthy in explaining why a high (low) inflation period is followed by a high (low) inflation period. That shed light on why the changes are more likely to be gradual than abrupt unless the occurrence of a shock.

It urges us to analyze the incidence of autocorrelation among the error terms, which violated one of the assumptions of the ordinary least square (OLS). Since the error term is an unobserved term, we cannot compute their autocorrelation; we rely on the correlogram of the residuals instead.

4.3.1. Analyzing the Stationarity

Unit Root Analyses

The unit roots analysis is meaningful because "it has been observed that most time series are DSP rather than TSP" (Nkoro & Uko, 2016, pg. 67). The authors mean DSP – Difference stationery Process (stationary after differentiation) and TSP – Trend Stationary Process (Deterministic). Moreover, as suggested by the scholars (2016, pg. 86), "the variables that are the integration of order I(2) lead to the crashing of the techniques". Besides, in the presence of unit root, any shock can trigger a permanent effect, preventing the possibility of making predictions.

A rough test to evaluate whether the series have or do not have a unit root is plotting a graph and, by the rules of the thumb, seeing if the observation is trendy or if the observations quickly convert to the mean. Nevertheless, there are specific techniques to assess the data stationarity, such as Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test, Phillips-Perron (PP) test, and Augmented Dickey-Fuller (ADF) test.

Mathematically, according to GUAJARATI (2011), given the autoregressive model, we can intuitively represent unit root as follows:

$$Y_t = \beta_1 + \beta_2 t + \beta_3 Y_{t-1} + u_t \text{ ------------------------ } (7)$$

After subtracting Y_{t-1} from both sides, transforming β_3 into C-1, and considering "u" as a residue and t as a trend, we have:

$$Y_t - Y_{t-1} = \beta_1 + \beta_2 t + (C - 1)Y_{t-1} + u_t, \text{ then: ---------------- } (8)$$

$\Delta Y = \beta_1 + \beta_2 t + (C - 1)Y_{t-1} + u_t$; if C is equal to 1, it means that β_3 is equal to zero, which yields no relationship between the dependent variable and its predecessor. Therefore, the unit root hypothesis consists of β_3 equal to zero, or H_0: $\beta_3 = 0$, and the alternative hypothesis is H_0: $\beta_3 \neq 0$. If we fail to reject the null hypothesis, we face a nonstationary time series.

This test can be done by the Dickey-Fuller method, and the hypothesis will be named the tau test (ƚ). It is essential to highlight that DF critical values do not follow the exact value of t-statistics. The tau (ƚ) depends on the kind of model chosen and the number of variables. Moreover, we will look at the left-tail side of the distribution.

The Dicky-Fuller and Augmented Dickey-Fuller are the main tests to determine whether the variable has a unit root. To that end (DF) presented three different forms of testing :

a) Random walk:

$$\Delta Y = \beta_3 Y_{t-1} + u_t \text{ ------------------------------------ } (9)$$

b) Random walk with drift (also known as slope or shift):

$$\Delta Y = \beta_1 + \beta_3 Y_{t-1} + u_t \text{ ------------------------------------ } (10)$$

c) Random Walk with drift and a deterministic trend, given t = 1,2, …t (the trend can be deterministic or stochastic):

$$\Delta Y_t = \beta_1 + \beta_2 t + \beta_3 Y_{t-1} + u_t \quad \text{-----------------------------} (11)$$

Before we move forward in explaining the DF test, it is crucial to clarify important aspects of the trend. It can be defined as a persistent upward or downward movement of variables over a period. Recognizing trends is vital because "Ignoring the fact that two sequences are trending in the same or opposite directions can lead us to falsely conclude that changes in one variable are actually caused by changes in another variable." (WOODRIDGE, 2013, pg. 364).

The trending behavior can be captured by β_2 in equation c, u_t, in this case, is an independent and identically distributed sequence with E $(e_t) = 0$ and Var $(e_t) = \sigma^2$. According to WOODRIDGE (2011), a trending behavior also can be explained by the simple equation:

$$Y_t = \alpha_0 + \alpha_1 t + e_t,\ t = 1,2,\ldots \quad \text{-------------------------} (12)$$

Holding everything else fixed, α_1 measures the changes, due to time, in Y_t from one period to the next. A linear correlation characterizes the equation above; nonetheless, exponential trends express many of the economic time series. In the occurrence of an exponential relationship, the theory suggests transforming the exponential variable into a natural logarithm to solve the inconsistency derived from an exponential relationship, assuming that the variables are greater than zero.

A trend in a time series can be a source of the nonstationary process, and this kind of time series characteristics encompasses different mean and variance for each piece of period. To the deterministic trend, each Y_i is impacted by β_2, positively or negatively, and β_2 is a fixed parameter given that Y changes due to the cumulative manner of simple changing of time. When we refer to stochastic tendency, β_2 is persistent and random.

For a time series to be considered stationary, the series has to have at least these three conditions :

$E(Y_t) = \mu$ ----------------- (13)

$Var(Y_t) = \sigma^2$ ------------------------------- (14)

$Cov(Y_t, Y_{t-1}) = \gamma_s$ ------------------------------ (15)

Where μ, σ^2, and γs, are constants, the mean and variance of Yt do not depend on the time. This process is also known as the white noise process. Therefore, the error term obeys what determines the equations 13, 14, and 15; if otherwise, the process is considered nonstationary. "The first feature that has received the most attention"… "Nonstationary series with nonconstant means are often described as not having the property of mean reversion" (Hill, 2011, pg. 477)

Dickey-Fuller test

Many tests assess the unit root issue; however, the DF test will be employed for Thai and Brazilian time series due to its reliability and popularity. Therefore, it is urged to analyze the following equation:

$$Y_t = \rho_1 Y_{t-1} + e_t, \ 0 < \rho_1 \leq 1 \quad \text{------------------ (16)}$$

The time serie represented by the equation above is considered a univariate time series. According to GRANGER & NEWBOLD (1974), univariate time-series models are examples of stochastic processes where the variable y is related to past values of itself and current and past error terms. As a univariate model, this model does not account for regressor as a multivariate model. Because of its simplicity, the univariate and autoregressive of order one – AR(1) is didactic in explaining the unit root issue. That equation is called AR (1) because the dependent variable is partly composed of just one lag of itself.

How to figure out if the series depicted by equation 16 is random walking or stationary autoregressive (1)? The hypothesis test will be as follows:

$$\mathbf{H_0{:}\rho_1 = 1}$$

$$\mathbf{H_1{:}\ \rho_1 < 1}$$

The first step is finding an estimated value of ρ, employing OLS regression. Then ρ* and Sρ* will represent the estimated regressor and standard error. After that define the ƚ-test (ƚ= (ρ* - 1)/ Sρ*)). Contrast the result with the values in the table constructed by Dickey and adopted by Fuller against the critical value of ƚ, considering the sample size. If $|\rho_1| > 1$, then the series has explosive behavior. If $|\rho_1| = 1$, than the series has unit root (non-stationary); and If $|\rho_1| < 1$ then the series is I (0), called, stationary. It is important to stress that the t-test is not useful in this situation; we will use the *tau* instead. Moreover, in this scenario, we analyze the distribution's left tail; the more negative, the more statistically significant.

The DF test has a sensitive flaw of not acknowledging that the error term might also be correlated; the Augmented DF (ADF) deals with this weakness. The ADF test assumes a serial autocorrelation in the error term. Therefore "they extend their test by including extra lagged in terms of the dependent variables in order to eliminate the problem of autocorrelation." (Mushtaq, 2011). In other words, to perform ADF, we should explore the explanatory variable lags until obtaining a white noise error. In order to choose the adequate number of lags, it is possible to use any valid criteria: AIC (Akaike), SBC (Schwarts), and HQ (Hanna-Quinn). The general equation will be as below.

$$\Delta Y_t = \beta_1 + \beta_2 t + \beta_3 Y_{t-1} + \sum_{i=1}^{m} \alpha \, \Delta Y_{t-1} \quad \text{------------------------} (17)$$

In sum, the importance of knowing whether the time series is stationary is because, otherwise, we can generate a regression with a significant coefficient and a large R^2 with two variables that are not correlated whatsoever. This process is denominated as spurious regression. In this scenario, the residues are probably correlated, and the *t*- statistics test is no longer reliable.

Integration

A Process stochastic nonstationary for a Y variable is called integrated posse in order *d*, or d I(d), when we have to differentiate in *d* times to turn it into a stationary process. In other words, a process integrated with I(O) is a purely stationary process since do not need to be integrated. (ENGLE and GRANGER, 1987).

4.3.2 Cointegration

Since a large amount of time series became stationary after differentiation methods, some long-term information can be lost in this process. "Cointegration makes it possible to retrieve the relevant long-run information of the relationship between the considered variable that had been lost on differencing." (NKORO & UKO, 2016, pg. 68)

Another angle to analyzing long relationships is to consider that sometimes, two time series, separately, have stochastic trend behavior. However, when these series are combined, they become stationary – I (0). "This linear combination cancels out the stochastic trend in two series." (JAGUARATI, 2011, pg. 230). An anecdotic example is the drunkards wandering, holding a dog by the dog leash, and randomly walking. However, even with the distance varying during the journey, it varies within a range. Something (the lash) holds the dog and the drunkards together long-term. In this metaphor, the path of the dog and the drunkards represents a nonstationary time series. Nevertheless, it is possible to visualize that the distance between those two time series is relatively constant. Even when the distance between those two variables varies in the short run, there is a long-run relationship between them. This long-run relationship is called Cointegration.

Using inappropriate techniques can lead to a spurious relationship between nonstationary variables. Therefore, Engle and Granger (1987) developed the cointegration test, later improved by Johansen (1988). The main difference between the unit root and cointegration tests is that the latest is performed to analyze the relationship among variables which shows the unit root. In this context, it deserves particular attention that Cointegration cannot be used when the variables present different orders of integration.

By way of explanation, suppose a bivariate regression:

$$e_t = Y_t - \beta_1 - \beta_2 X_t, \qquad \text{---------------------- (18)}$$

To test if these two variables are cointegrated, we can test for the stationarity of the Least Square Residuals ($\hat{e}$) using a Dickey-Fuller test. If the residuals are stationary, those two variables are cointegrated; otherwise, any regression would be spurious if the residuals are not stationary.

In a time series, each observation is probably highly correlated with its own lag; for a stationary process, this correlation between adjacent terms should be the same across all periods. To perform the DF test, we must evaluate whether there is a trend or intercept in the regression to choose the critical values. The test consists of:

H_0: residuals are nonstationary. $\Longrightarrow$ The series are not cointegrated

H_1: residuals are nonstationary. $\Longrightarrow$ The series are cointegrated.

Likewise, for the unit root one-tail test, we will look at the left side of the distribution and reject the null hypothesis if *tau* statistics is smaller than the critical value.

Additionally, there is another test to assess Cointegration, called Johansen Cointegration Test. "Johansen cointegration test method is employed when all the variables included in the model are nonstationary. In the case of mixed variables, i.e., some variables stationary but others nonstationary cointegration method cannot be used." Shrestha & Bhatta (2018, pg. 18)

Nevertheless, in some moments, even sharing a long-run trend, those kinds of time series can deviate from the equilibrium in the short run. That is why was created the Error Correction Model.

4.3.3 Error Corrector model

"A relationship between I(1) variables is also often referred to as a long-run relationship while a relationship between I(0) variables is often referred to as a short-run relationship" (Hill, 2011, pg. 490). Error correction is how cointegrated variables would return to their typical path. Consider a nonstationary bivariate equation:

$Y_t = \delta + \theta_1 y_{t-1} + \delta_0 x_t + \delta_1 x_{t-1} + v_t$ ------------------------------- (19)

Since we define Y and X as cointegrated, there is a long-run relationship between them. Therefore: $y_t = y_{t-1} = y$, $x_t = x_{t-1} = x$ and $v_t = 0$.

Considering that: $Y = \beta_1 + \beta_2 x$, $\beta_1 = \delta / (1 - \theta_1)$, and $\beta_2 = (\delta_0 + \delta_1) / (1 - \theta_1)$. Then, we can accommodate the cointegrating relation into ARDL. First let us manipulate the equation by adding the term y_{t-1} in both side.

$y_t - y_{t-1} = \delta + (\theta_1 - 1) y_{t-1} + \delta_0 (x_t + x_{t-1}) + (\delta_0 + \delta_1) x_{t-1} + vt$ ------------ (20)

$\Delta y_t = (\theta_1 - 1) (\delta/(\theta_1 - 1) + y_{t-1} + (\delta_0 + \delta_1) x_{t-1/} \theta_1 - 1) + \delta_0 \Delta x_t + v_t$ -------------- (21)

Using β_1 and β_2 definitions:

$\Delta y_t = -\alpha (y_{t-1} - \beta_1 - \beta_2 x_{-1}) + \delta_0 \Delta x_t + v_t$ --------------------------(22)

If we consider $\alpha = (1 - \theta_1)$, the cointegration relationship is inserted into the ARDL framework. The expression $(y_{t-1} - \beta_1 - \beta_2 x_{-1})$ shows the deviation from the long-run, and $\theta_1 - 1$ indicates the correction. This equation suggests an important conclusion. First, if the error in the previous period was positive (y_{t-1}), then the y_t will fall, and the first difference will be negative. Second, if the error in the previous period were negative (y_{t-1}), y_t would increase, and the variation will be positive. (Hill, 2011, pg. 491)

$Y_{t-1} > \beta_0 + \beta_1 x_{t-1},$ then $y_{t-1} > 0$, and $\Delta_y < 0$ -------------------- (23)

$Y_{t-1} < \beta_0 + \beta_1 x_{t-1},$ then $y_{t-1} < 0$, and $\Delta_y > 0$ ---------------------- (24)

In sum, if the variable were not stationary, we can estimate its parameters by:

a) ARDL: when there is a Trend Stationarity or a stochastic trend, the variables are not cointegrated (estimate the model in first differences).
b) Cointegration: If the variables are cointegrated, it is possible to estimate the long-run relationship and the error correction model to estimate the short-run relationship.

4.3.4 ARDL or Bound Cointegration Test

The ARDL or Bound Cointegration test model was proposed by Pesaran and Shin (1995). The model can be split into short-run autoregressive, short-run distributed lags, and long-run. Furthermore, this model is a "p" (lag of dependent variable) and "q" (lag of independent variables) model, and the short run can be mathematically expressed as follows:

$Y_t = \delta + \theta_1 Y_{t-1} + \ldots. + \theta_p Y_{t-p} + \delta_0 X_t + \delta_1 X_{t-1} + \ldots + \delta_q X_{t-q} + v_t$ ---------- (25)

$\delta + \theta_1 Y_{t-1} + \ldots. + \theta_p Y_{t-p}$ Autorregressive Component

$\delta_0 X_t + \delta_1 X_{t-1} + \ldots + \delta_q X_{t-q}$ Distributed Lag Component

When the number of lags is adequate, it reduces the serial correlation of the errors. The correlogram of the residues is a helpful tool to check this kind of autocorrelation. For a white noise error term, the *v* must consist of a random error that assumes zero means and constant variance.

The ARDL method deals with short and long-run in a single equation. For this last relationship, the studies of Pesaran and Shin (1995) are essential in the matters that it helps identify the existence of a cointegration vector. In the word of NKORO and UKO (2016, pg. 75): "If one cointegrating vector (i.e., the underlying equation) is identified, the ARDL model of the cointegrating vector is reparametrized into ECM."

$\Delta Yt = \delta + \sum_{i:1}^{p} \theta \Delta Yt - i + \sum_{i:0}^{q} \delta \Delta xt - i + + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-1} + v_1$ ----------- (26)

In sum, a bound testing procedure is available to draw conclusive inferences without knowing whether the variables are integrated of order zero or one, I(0) or I(1), respectively (Pesaran, Shin, and Smith, 2001). The model will expand to (p, $q_{1,}$ and q_2).

$\delta + \sum_{i:1}^{p} \theta \Delta Yt - i + \sum_{i:0}^{q} \delta \Delta xt - i +$ $\Longrightarrow$ SHORT RUN

$\varphi_1 Y_{t-1} + \varphi_2 Y_{t-1} + v_1$ $\Longrightarrow$ LONG RUN/ERROR CORRECTION

The hypothesis for the long-run relationship is tested as:

$H_0: \varphi_1 = \varphi_2 = 0$ No long relationship

$H_1: \varphi_1 \neq \varphi_2 \neq 0$ There is a long relationship

To reject the null hypothesis is necessary to assess the two sets of F-statistic. The first set presumes that all variables are integrated I(0), then there is no cointegration. The second set assumes that all variables are I (1). The critical values are the ranges of: 2.496 - 3.346, 2.962 – 3.910, and 4.068 – 5.250 at 90%, 95%, and 99%, respectively. If the F-statists of φ_1 and φ_2 lie within that bound, the results are inconclusive. However, suppose the F-statistics lies bellow the lower bound, it means you cannot reject the null hypothesis. On the other hand, if the F-statistic's lies above the upper bound, we cannot reject the null hypothesis.

4.4 Model Proposed

Since the scope of this work is to evaluate a short-run period (2020 and 2021), the effort will be concentrated on the first part of equation 26.

The models displayed in sections 4.4.1 and section 4.4.2 will help answer the research question by means of a comparison of the coefficients **δ (delta) and θ (theta)**. These coefficients will disclose the magnitude of importance in which each variable has impacted the inflation variation.

4.4.1 Brazilian Model

$$\mathbf{BF\&BINF} = \boldsymbol{\delta} + \sum_{i=1}^{p} \boldsymbol{\theta}_{1+t}\, BF\&INF_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{2+t}\, BNEER_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{3+t}\, BAPI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{4+t} BAPROD_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{5+t}\, IBCBR_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{6+t}\, BEINF_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{7+t}\, COI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{8+t}\, COP_{t-I} + \sum_{i=o}^{q} \boldsymbol{\delta}_{9+t}\, GFI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{10+t}\, BFIMP_{t-i} + \sum_{i=o} \boldsymbol{\delta}_{11+t}\, BFEXP_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{12+t}\, BER_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{13+t}\, BIR_{t-i} + e_{t-1}$$

4.4.2 Thai Model

$$\mathbf{TF\&BINF} = \boldsymbol{\delta} + \sum_{i=1}^{p} \boldsymbol{\theta}_{1+t}\, TF\&INF_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{2+t}\, TNEER_{t-i} + + \sum_{i=o}^{q} \boldsymbol{\delta}_{3+t}\, TAPI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{4+t} TAPROD_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{5+t}\, LEI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{6+t}\, TEINF_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{7+t}\, COI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{8+t}\, COP_{t-I} + \sum_{i=o}^{q} \boldsymbol{\delta}_{9+t}\, GFI_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{10+t}\, TFIMP_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{11+t}\, TFEXP_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{12+t}\, TER_{t-i} + \sum_{i=o}^{q} \boldsymbol{\delta}_{13+t}\, BIR_{t-i} + e_{t-1}$$

Table 6 *- Variables Abbreviation*

Abbreviation	**Meaning**
(B)(T)F&BINF	Food & Beverage Inflation
(B)(T)NEER	Nominal Effective Interest Rate
(B)(T) API	Agricultural Price Index
(B)(T) APROD	Agricultural Production Index
IBC-BR	Economic Activity Indices
(B)(T)FIMP	Food Imports
(B)(T) FEXP	Food Exports
LEI	Leading Economic Index
(B)(T) IR	Interest Rate
(B)(T)ER	Exchange Rate
GFI	Global Food Index
COI	Crude Oil Index
COP	Crude Oil Price

CHAPTER 5

RESULTS AND DISCUSSION

This chapter will be composed of three sections. The first section will present the process related to the Brazilian data analysis and how was the data scrutinized and transformed to meet the criteria of reliability, consistency, and non-bias. For this purpose, all selected variables will be tested, in their raw format and logarithmic form, to determine whether they have unit roots. The variables which do not pass on ADF tests will be integrated by differencing. After this process, the variables that do not meet stationarity requirements will be dismissed. Then, a correlogram matrix will be performed to identify the highly correlated variables. The correlogram results can prevent building a model carrying regressors that could cause multicollinearity. Thereafter, all dependent variables will be tested for granger causality to assess which variables are more capable of forecasting the dependent variable behavior. This will be helpful in choosing which variables are more relevant to be included in the model.

The number of lags will be defined by applying the AIC (Akaike Information Criteria). The AIC is based upon two parts: the first part is a penalization for the excess of terms (2k), and the second part is the log-likelihood ($-2\ln(L)$), which refers to how well the model is fitted. Thus, these criteria penalize the insertion of useless variables or lags and avoid an over-fitted model. Follow below the general equation, given that: N is the number of observations, SSe is the sum square of errors, and K stands for the number of parameters.

$$AIC = N * \ln (SS_e / N) + 2K$$

After that, the ARDL methodology will be applied for each model and the residuals will be checked on whether they hold the assumptions for normality, homoscedasticity, autocorrelation, and multicollinearity. If the model meets the regression assumptions, it will be tested for long-term cointegration.

The second section will present the findings and model analyses concerning Thailand, using, as much as possible, the same criteria applied to Brazil's diagnostic. The third section will assess, confront, and analyze both countries' findings. Finally, the fourth section will present the response to the research question and final considerations. It is important to stress that all statistical calculation was done on Eviews, v.12 software, and the statistical significance adopted in this study will be 0.05%. All raw data can be found in Appendix A of the present study, whereas the statistical summaries will be available in Appendix B.

5.1) Brazil's Findings and Model Analysis

Based on the literature review, as stated in chapter 4, the following variables will encompass the explanatory regressors: Agricultural Price Index, Agricultural Production Index, Energy Inflation, Exchange Rate, Food & Beverage Imports, Food & Beverage Exports, Interest Rate, Nominal Effective Exchange Rate, Crude Oil Index, Crude Oil Price, Global Food Index, and a proxy for monthly domestic output - IBC_BR. These raw data are available in Appendix A.

A test for stationarity was conducted using Augmented Dickey-Fuller, as stated in section 4.3.1 of this study. This test's statistical summary is available in Table B-1, Appendix B. The Null Hypothesis consists of: the variable has a unit root. To reject this hypothesis, a significance of 0.05 was used as the cutoff point. Additionally, the stationarity of the logarithmic form of the variables mentioned in the previous paragraph was also tested. The logarithmic transformation is helpful to cope with skewness, to change exponential growth into linear growth, and to facilitate the comparison among variables with different magnitudes. When we failed to reject the null hypothesis, either in the raw form or the logarithmic form, we took the first difference of these variables. Therefore, this group of variables will be I(0) and I(1). The table below shows the variables that met the requirements for stationarity I(0) or I(1) and their abbreviation as they appear in the statistical summaries.

Table 7- *The abbreviation of stationary Variables I (0) or I (1)*

BF_INF DIFBF_INF	• Brazilian Food & Beverage Inflation • First Difference of the BF_BINF
BENINF DIFBENINF	• Brazilian Energy Inflation • Fist Difference of BENINF
BIR LNBIR	• Brazilian Interest Rate • Log BIR
IBC_BR LNIBC_BR DIFIBC_BR LNIBC_BR DIFLNIBC-BR	• Economic Activities Index • Log Economic Activities Index • First Difference of IBC_BR • Log of IBC_BR • First Difference of LNIBC_BR
LNBF_BEXP DIFBF_BEXP	• Log of the Brazilian Food & Beverage Export • First Difference of LNBF_BEXP
LNBAPI DIFBAPI DIFLNBAPI	• Brazilian Agricultural Price Index • First Difference of the Brazilian Agricultural Price Index • First Difference of the Log of BAPI
LNBAPROD DIFBAPROD DIFLNBAPROD	• Log of Brazilian Agricultural Production • First difference of the Brazilian Agricultural production

Table 7- *The abbreviation of stationary Variables I (0) or I (1)*

	• First Difference of the Log of BAPROD
LNBF_BIMP DIFBF_BIMP DIFLNBF_BIMP	• Log Brazilian Food & Beverage Imports • First Difference of the Brazilian Food & Beverage Imports • First difference of the log of BF_BIMP
BER DIFBER DIFLNBER	• Brazilian Exchange Rate • First Difference of the Brazilian Exchange Rate • First Difference of the Log of BER
BNEER LNBNEER DIFBNEER DIFLNBNEER	• Brazilian Nominal Effective Exchange rate • Log BNEER • First Difference of the Brazilian Nominal Effective Exchange Rate • First Difference of Log of BNEER
COI DIFCOI	• Crude Oil Index • First Difference of the Crude Oil Index
COP LNCOP DIFCOP DIFLNCOP	• Crude Oil Price • Log of Crude Oil Price • First Difference of the Crude Oil Price • First Difference of the Log of the COP
DFI LNGFI DIFGFI DIFLNGFI	• Global Food Index • Log Global Food Index • First Difference of the Global Food Index • First Difference of the Global

To build the models, we use three main criteria. First, a correlation matrix was calculated, tables B-4, B -5, B -6, and B -7, in Appendix B. Second, the Granger causality test of the dependent variable was applied against each independent variable to assess whether a specific variable helps predict the former variable. While correlation refers to relationships, granger causality assesses whether one variable is caused by another. This result contributes to choosing the model with more explanatory power. Third, the equations will try to encompass, as much as possible, variables from the real economy, such as Agrarian Production, Energy, and Crude Oil, and variables from the monetary stance, such as Interest Rate, Exchange Rate, and Nominal Effective Exchange Rate.

The correlation matrix quantifies and qualifies the relationship between two variables. Pearson's correlation coefficient varies from -1 (maximum negative correlation) to + 1 (maximum positive correlation). This matrix can be a tool for preventing multicollinearity, displaying the degree of correlation among the variables. This tool allows us to spot which combination of variables might cause multicollinearity. For many scholars, a Pearson coefficient, with an absolute value above 0.7, determines a strong relationship between two variables. Analyzing the correlogram A, B, C, and D (tables B-4, B-5, B-6, and B-7), it is possible to verify that no strong relationship was found among the regressors. However, we can highlight some moderate correlations that vary from the absolute value of 0.3 to 0.7. The table below shows the list of variables with a moderated bivariate correlation:

Table 8 - *Brazilian variables: Moderate correlation*

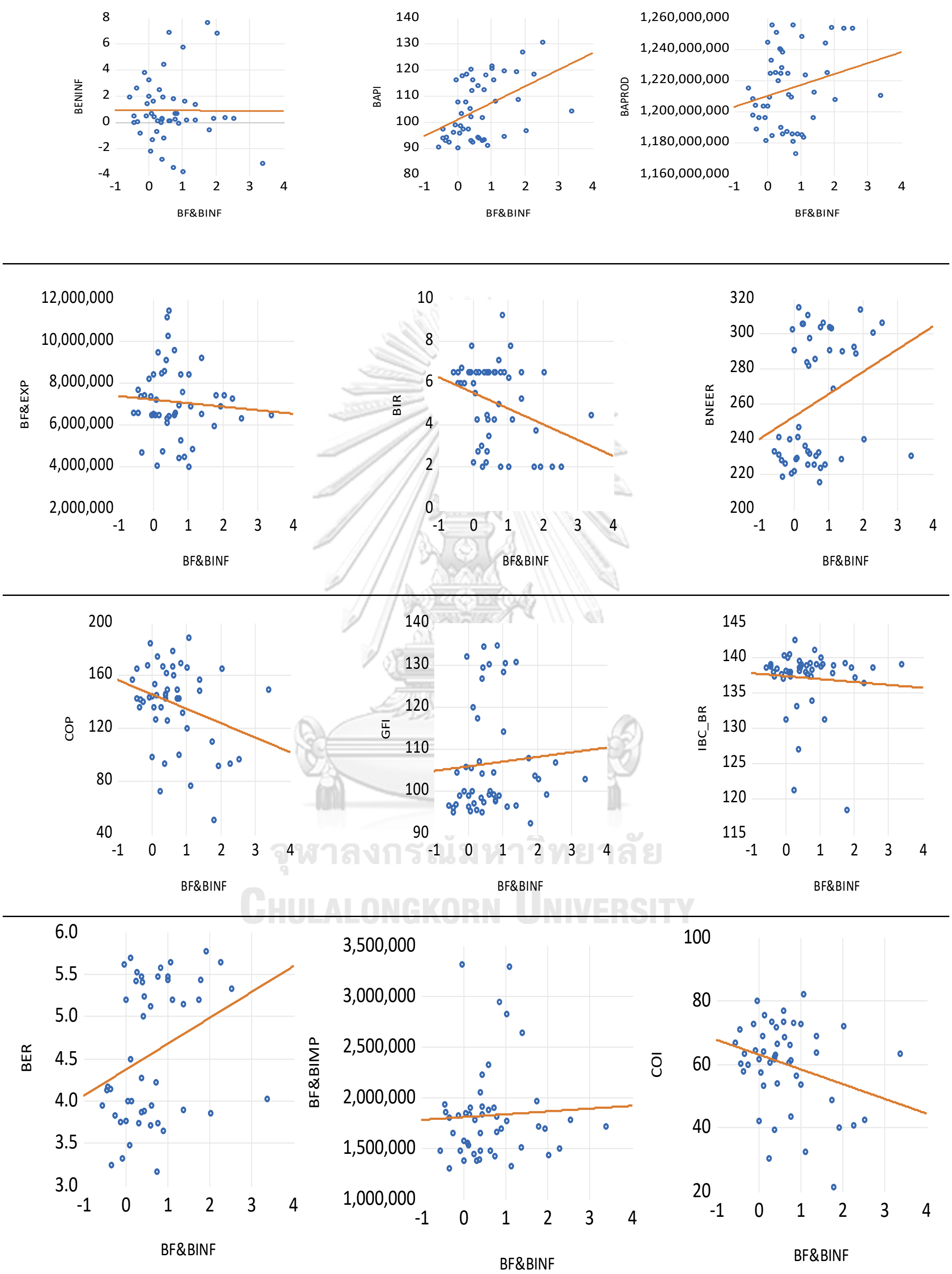
Interest Rate	• F_BINF (negative) • GFI (negative)
Energy Inflation:	First Difference of the Logarithm of: • BAPI (negative). • BAPROD (negative), and • DIFLNFIMP (positive).
GDP proxy	• DIFBNEER (negative) • DIFLNBFEXP (negative) • DIFLNBNEER (negative)
First Difference of the Crude Oil Index and Crude Oil Price	• DIFIBC_BC (positive) • DIFLNBER (negative) • DIFLNIBC-BR (positive) • DIFLNDFI (negative)
First Difference of the Logarithm of the Brazilian Agricultural Price Index	• BNEER (positive) • DIFCOI and DIFCOP (negative)

Note. The coefficients can be found in Appendix B, tables B-4 to B-7.

The contemporaneous negative relationship between interest rate and domestic food inflation is not in line with the literature because, according to Taylor's rule, "the federal funds should be set equal to the inflation rate plus an equilibrium real federal funds rate." (pg 464, MISHKIN, 2012). This result might be because of the central bank's dual mandate - inflation and employment. Along with the Pandemic, a sharp drop in GDP might have prevented the Brazilian Central Bank from raising the interest rate.

The Agricultural Price index and the Production Index have a positive relationship with food inflation. The first highlights a high pass-through from agricultural costs to retail prices. With respect to Production, those correlations might be spurious. Regarding the fact that the Nominal Effective Exchange Rate and the Exchange Rate are positively related to the variable of interest, this is expected, once currency depreciation is the main cause of price pressure. It is important to stress that, unlike Thailand, an increase in Brazil’s BNEER means depreciation. The negative relationship of crude oil and food inflation is unexpected and needs more investigation. For imports, exports and energy inflation, the curve is quite flat, which implies non-correlation.

Figure 11 - *Scatterplot. Food and Beverage Inflation against the explanatory variables*



Additionally, the granger causality test was performed to evaluate which variables are more likely to have high explanatory power. Hence, table 09 displays the more expressive results:

Table 9 - *Pairwise Granger Causality Test*

Hypothesis	Obs.	lags	F. Statistics	Probability
IBC_BR does not Granger Cause BF_BINF BF_BINF does not Granger Cause IBC_BR	44	4	2.19581 2.93963	0.0896 0.0340
DIFGFI does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFGFI	43	4	1.70459 2.48061	0.1717 0.0623
DIFIBC_BR does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFIBC_BR	43	4	3.88782 0.37566	0.0105 0.8244
DIFLNGFI does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFLNGFI	43	4	1.62353 0.1909	2.50098 0.0607
DIFLNIBC_BR does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFLNIBC_BR	39	4	2.71465 0.80396	0.0303 0.6059
BIR does not Granger Cause BF_BINF BF_BINF does not Granger Cause BIR	40	8	3.70516 0.37955	0.0064 0.9206
DIFBER does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFBER	39	8	2.79218 1.40431	0.0269 0.2493
DIFGFI does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFGFI	39	8	0.84075 2.59807	0.5776 0.0364
DIFLNBAPI does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFLNBAPI	39	8	2.75965 0.79099	0.0283 0.6160
DIFLNBFIMP does not Granger Cause BF_BINF BF_BINF does not Granger Cause DIFLNBFIMP	39	8	0.52094 2.05200	0.8279 0.0871

Note. The whole table can be found in Appendix B, tables B-2 and B-3

Broadly speaking, granger causality means that the past values of X_t contain information capable of predicting the contemporaneous value of Y. The F-statistics - the joint significance of the coefficients - allow us to reject the null Hypothesis. Therefore, we can state that there might be a unidirectional granger causality of IBC_BR (DGP proxy), Interest Rate, and Agrarian Price Index to food inflation. These findings partially corroborate the correlogram analysis regarding the impact of the Interest Rate on Food Inflation. Besides, we can stress that the explanatory power of the proxy for GDP is an unexpected outcome because scholars rarely correlate growth output and food inflation. Nevertheless, a more complex test will be done to investigate whether these two variables are upon a spurious relationship.

Moreover, the Chow test was performed to assess the existence of a structural break for the Food & Beverage inflation series. As seen below, the F-statistics was insufficient to reject the null Hypothesis, which states: no breaks in January 2020. Therefore, there is no breakpoint in that time series that justifies the use of dummies.

Table 10 - *Test for structural break*

Chow Breakpoint Test: 2020M01
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 2018M01 2021M12

F-statistic	3.709314	Prob. F(1,46)	0.0603
Log likelihood ratio	3.722444	Prob. Chi-Square(1)	0.0537
Wald Statistic	3.709314	Prob. Chi-Square(1)	0.0541

After the preliminary analyses for unit roots, granger causality, and correlation; and after assessing the residual's consistency for normality, non-serial correlation, homoscedasticity, non-multicollinearity, and stability, four models were selected:

1) $BF\_BINF = \delta_0 + \theta_1 BF\_BINF_{t-1} + \delta_1 \Delta lnBAPROD_{t-6} + e_t$

2) a)$BF\_BNIF = \delta_0 + \theta_1 BF\_BINF_{t-1} + \delta_1 \Delta lnBAPI_{t-1} + \delta_2 BENINF_{t-1} + e_t$

   b)$BF\_BNINF = \delta_0 + \delta_1 \Delta lnBAPI_{t-1} + \delta_2 BENINF_{t-1} + e_t$

3) $BF\_BNINF = \delta_0 + \theta_1 BF\_BINF_{t-1} + \delta_1 BENINF_{t-2} + \delta_2 \Delta lnBNEER_{t-7} + e_t$

5.1.1 Model 1: Production and Interest Rate as the explanatory variable.

Many attempts have been made with the Exchange Rate variable, as seen in Table B-19, Appendix B. However, whatever form used, the model encompassing the exchange rate was not normally distributed or showed a nonsense coefficient sign. For the models in which the assumptions were observed, the coefficient for exchange rate was negatively related to food inflation, which contradicts the literature and the correlation matrix. Recall that the exchange rate is calculated by dividing the domestic currency by the foreign currency. Thus, the interest rate was chosen instead of the exchange rate because the former brought more instability to the model.

Therefore, Model 1 encompasses two explanatory variables: Interest Rate (BIR) as fixed and the Difference of the Logarithm of the Agricultural Production Index (ΔlnBAPROD). The autoregressive component (1 month of lag) and Agricultural Production Index (6 months of lag) showed statistical significance. The coefficient relative to the interest rate (BIR) did not display any significance; nevertheless, the model with interest rate had a higher Adjusted R-square than the model without that variable. The adjusted R-squared of 0.36% indicates that approximately 36% of the variation in Food Inflation can be explained by the variation in the regressors. Furthermore, the F-statistics – the overall significance in regression – allow us to reject the null Hypothesis: the intercept-only model fits the data as well as the present model. The coefficient of the autoregressive part is highly significant (at 1%) and positively correlated. In turn, the Agrarian Production displayed, with 6 months of lag, has statistical significance (1%) and a negative relationship with the dependent variable.

Table 11 - *BRAZIL MODEL 1 – SHORT RUN*

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/08/22 Time: 13:48
Sample (adjusted): 2018M09 2021M12
Included observations: 40 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): DIFLNBAPROD
Fixed regressors: BIR C
Number of models evaluated: 36
Selected Model: ARDL(2, 7)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.628825	0.178874	3.515459	0.0015
BF_BINF(-2)	-0.270375	0.159991	-1.689937	0.1021
DIFLNBAPROD	-8.355262	14.99318	-0.557271	0.5818
DIFLNBAPROD(-1)	-20.88914	15.27945	-1.367139	0.1825
DIFLNBAPROD(-2)	26.49288	16.00176	1.655623	0.1090
DIFLNBAPROD(-3)	-2.336498	16.85369	-0.138634	0.8907
DIFLNBAPROD(-4)	-30.01486	18.55838	-1.617321	0.1170
DIFLNBAPROD(-5)	19.82238	15.66827	1.265129	0.2163
DIFLNBAPROD(-6)	-52.95688	15.53136	-3.409675	0.0020
DIFLNBAPROD(-7)	20.63356	17.06528	1.209096	0.2367
BIR	-0.122659	0.082101	-1.493991	0.1464
C	1.052284	0.475014	2.215269	0.0350

R-squared	0.546428	Mean dependent var	0.718000
Adjusted R-squared	0.368238	S.D. dependent var	0.834350
S.E. of regression	0.663170	Akaike info criterion	2.259754
Sum squared resid	12.31424	Schwarz criterion	2.766417
Log likelihood	-33.19507	Hannan-Quinn criter.	2.442947
F-statistic	3.066559	Durbin-Watson stat	1.912071
Prob(F-statistic)	0.008120		

The residual's analyses indicate that these coefficients are unbiased and reliable and hold the main assumptions for regression: linear in parameters, homoscedasticity, independent error term, normal error, no multicollinearity, and exogeneity. The whole summary of these tests can be found in Appendix B.

The Q-statist test and Breusch-Godfrey Serial Correlation LM test, table B-8 and table B-09, have shown the absence of serial correlation in the model. The Q-statistic test outcome had a p-value greater than 10%. For its part, the Breusch-Godfrey Serial Correlation LM Test corroborated the Q-statist. The null hypothesis states: there is no serial correlation at up to 8 lags. The F-statistics probability does not allow us to reject the null hypothesis; therefore, there is no indication of serial correlation. For heteroscedasticity, the Breusch-Pagan-Godfrey results fail to reject the null Hypothesis: there is homoscedasticity.

Null hypothesis: Homoskedasticity

F-statistic	0.957972	Prob. F(11,28)	0.5041
Obs*R-squared	10.93754	Prob. Chi-Square(11)	0.4485
Scaled explained SS	4.764450	Prob. Chi-Square(11)	0.9420

Furthermore, the model has proved to be stable, the errors normally distributed, and free from the presence of multicollinearity, as seen in table B-11 a, B-11,b, and B-11c, in Appendix B. The Jarque-Bera probability was 0.8, greater than 0.05; therefore, the error terms are normally distributed. The outcome of the centered Variance Inflation Factor's (VIF) for all variables was below the cutoff number of VIF 3. The CUSUM test shows no structural break in the model.

After that, we shall test whether there is a long-run relationship between the dependent and independent variables. To this end, a long-run bound test was performed.

H_0 : $\varphi_1 = \varphi_2 = 0$ No long relationship

H_1: $\varphi_1 \neq \varphi_2 \neq 0$ There is a long relationship

Table 12 - *Bound Test for long-run cointegration*

F-Bounds Test	Null Hypothesis: No levels relationship			
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	8.936234	10%	4.04	4.78
k	1	5%	4.94	5.73
		2.5%	5.77	6.68
		1%	6.84	7.84
		Finite Sample: n=45		
Actual Sample Size	41	10%	4.225	5.02
		5%	5.235	6.135
		1%	7.74	8.65

The figure above is only a fraction of table B-12, Appendix B. The F-statistics above the upper bound allow us to reject the null hypothesis, concluding that there is a long-term relationship among the variables.

5.1.2 Model 2: Agrarian Price Index and Energy Inflation

Model 2 sought to build an equation with the right-side part: the Global Food Index (GFI), Crude Oil, Brazilian Agricultural Price Index (BAPI), and Brazilian Energy Inflation (BENINF). Nevertheless, GFI as COI did not display any statistical significance. These two variables were substituted by others capable of measuring the international environment. Then a model was built with BAPI, BENINF, and Brazilian Exchange Rate (BER). Nonetheless, although the latter variable has shown a significant coefficient, this variable has disturbed the model. The presence of BER caused multicollinearity. Additionally, in attempting to stabilize the model by log transformation and first differencing, the coefficient turned into a negative sign, which is not in line with the literature. The summary of these models can be found in Appendix B, Table B-16.

Finally, the chosen model only counts on Agricultural Price Index and Energy Inflation and Food Exports. The food exports, as well as their log transformations and differencing, did not have a significative coefficient; however, it did not cause noise in the model. The statically significant variables' coefficients – Agricultural Price Index and Energy Inflation – are positively related to the dependent variable, in line with the scholars' views. As seen in appendix B, table B-17, the model is stable, and the residuals are well-shaped. The Jarque-Bera normality test outcome had a probability of 0.75. The Breusch-Godfrey for Serial Correlation test resulted in a 0.68 probability. Additionally, the Breusch-Pagan-Godfrey result was 0.49. These results, respectively, did not allow us to reject the null hypothesis of normality, no serial correlation, and homoscedasticity.

Table 13 - *Brazilian Model 2a.*
i)) Short-run, ii) Long-Run. Bound test for cointegration

i)

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/13/22 Time: 06:02
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNBF_BEXP DIFLNBAPI DIFBENINF
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 1, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.306232	0.124470	2.460293	0.0184
LNBF_BEXP	-0.496470	0.447999	-1.108194	0.2746
DIFLNBAPI	4.612862	3.624885	1.272554	0.2107
DIFLNBAPI(-1)	13.76909	3.653784	3.768446	0.0005
DIFBENINF	0.022492	0.040338	0.557600	0.5803
DIFBENINF(-1)	0.092941	0.038207	2.432584	0.0197
C	8.195527	7.078748	1.157765	0.2540

R-squared	0.471731	Mean dependent var	0.663696
Adjusted R-squared	0.390459	S.D. dependent var	0.842642
S.E. of regression	0.657877	Akaike info criterion	2.139671
Sum squared resid	16.87929	Schwarz criterion	2.417943
Log likelihood	-42.21244	Hannan-Quinn criter.	2.243913
F-statistic	5.804333	Durbin-Watson stat	1.829233
Prob(F-statistic)	0.000216		

*Note: p-values and any subsequent tests do not account for model selection.

ii)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	12.67826	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
		Finite Sample: n=50		
Actual Sample Size	46	10%	2.873	3.973
		5%	3.5	4.7
		1%	4.865	6.36
		Finite Sample: n=45		
		10%	2.893	3.983
		5%	3.535	4.733
		1%	4.983	6.423

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-5.573790	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

Notwithstanding this, when the export variable is removed from the model, the adjusted R-squared has improved. On the other hand, the autoregressive component has become statistically insignificant.

Table 14 - *MODEL 2b. Short-run*

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/11/22 Time: 13:23
Sample (adjusted): 2018M05 2021M12
Included observations: 44 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNBAPI DIFBENINF
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 3, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.235496	0.137340	1.714700	0.0950
DIFLNBAPI	4.729918	3.559046	1.328985	0.1922
DIFLNBAPI(-1)	17.42341	3.775129	4.615315	0.0000
DIFLNBAPI(-2)	-2.544515	3.872322	-0.657103	0.5153
DIFLNBAPI(-3)	6.138256	3.359210	1.827291	0.0760
DIFBENINF	0.029611	0.037922	0.780849	0.4400
DIFBENINF(-1)	0.121703	0.039420	3.087325	0.0039
C	0.423732	0.126113	3.359924	0.0019

R-squared	0.555166	Mean dependent var	0.693409
Adjusted R-squared	0.468670	S.D. dependent var	0.849703
S.E. of regression	0.619369	Akaike info criterion	2.042733
Sum squared resid	13.81023	Schwarz criterion	2.367131
Log likelihood	-36.94013	Hannan-Quinn criter.	2.163036
F-statistic	6.418433	Durbin-Watson stat	1.956579
Prob(F-statistic)	0.000062		

The F-statistics ensures that at more than 1% of significance, Model 2b has a better fit to the data than an alternative model without any independent variable. The model can explain approximately 46% of the variation of the dependent variable. The residuals are normally distributed and do not show heteroskedasticity or serial correlation. The Jarque-Bera has a probability of 0.79, failing to reject the null Hypothesis. The Breusch-Pagan-Godfrey test presented a chi-square larger than 0.05. Likewise, the Q-statistic test results fail to reject the null hypothesis of no autocorrelation. The summaries are in Appendix B, table B-13. Moreover, as verifiable in table B-14, appendix B, the centered Variance Inflation Factors (VIF) outcomes for each variable were less than 2, which indicates a neglectable multicollinearity level. Lastly, the CUSUM did not spot any structural break.

The bound test for long-run cointegration displayed a high level of significance in rejecting the null hypotheses. The F-statistics was 12.17, which is high above the upper bound at any level of significance, as seen below. The respective table is available in appendix B, table 15-B.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	12.17903	10%	3.17	4.14
k	2	5%	3.79	4.85
		2.5%	4.41	5.52
		1%	5.15	6.36
			Finite Sample: n=50	
Actual Sample Size	46	10%	3.333	4.313
		5%	4.07	5.19
		1%	5.817	7.303
			Finite Sample: n=45	
		10%	3.33	4.347
		5%	4.083	5.207
		1%	5.92	7.197

5.1.3 Model 3: Energy Inflation and Nominal Effective Exchange Rate as the explanatory variable.

The third model will consider a maximum lag of 8 due to the results of the granger causality test that pointed out granger causality between these explanatory variables and dependent variables with that specific lag. Energy inflation was used in its raw form, and the Nominal Effective Exchange Rate was used in its logarithmic form and then the first differencing was applied. The statistically significant coefficient had a positive sign, which aligns with the theory. The Adjusted R-squared was 0.35, which means that the model can explain 35% of the variation on the independent variable. In turn, the F-statistics of 0.04 allows for rejecting the null hypothesis that an alternative model with no variables would have a better fit than the present model.

Table 15 - *Brazilian model 3 – Short-run*

Dependent Variable: BF_BINF
Method: ARDL
Date: 09/28/22 Time: 11:10
Sample (adjusted): 2018M09 2021M12
Included observations: 40 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): BENINF DIFLNBNEER
Fixed regressors: C
Number of models evaluated: 324
Selected Model: ARDL(2, 7, 7)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.674921	0.183090	3.686282	0.0014
BF_BINF(-2)	-0.294508	0.178268	-1.652059	0.1134
BENINF	-0.050306	0.059794	-0.841308	0.4097
BENINF(-1)	0.149502	0.058257	2.566271	0.0180
BENINF(-2)	-0.092375	0.056211	-1.643347	0.1152
BENINF(-3)	0.019408	0.055858	0.347452	0.7317
BENINF(-4)	0.009574	0.052056	0.183909	0.8558
BENINF(-5)	0.007235	0.052196	0.138612	0.8911
BENINF(-6)	-0.061250	0.056954	-1.075419	0.2944
BENINF(-7)	0.122911	0.059607	2.062009	0.0518
DIFLNBNEER	-0.717952	3.133520	-0.229120	0.8210
DIFLNBNEER(-1)	3.588063	3.424033	1.047906	0.3066
DIFLNBNEER(-2)	-1.310389	3.474641	-0.377129	0.7099
DIFLNBNEER(-3)	-0.756160	3.480644	-0.217247	0.8301
DIFLNBNEER(-4)	6.144343	3.384862	1.815242	0.0838
DIFLNBNEER(-5)	-4.063500	3.417040	-1.189187	0.2476
DIFLNBNEER(-6)	3.681216	3.542366	1.039197	0.3105
DIFLNBNEER(-7)	8.946673	3.613021	2.476231	0.0219
C	0.272963	0.209772	1.301236	0.2073

R-squared	0.653596	Mean dependent var	0.718000
Adjusted R-squared	0.356678	S.D. dependent var	0.834350
S.E. of regression	0.669210	Akaike info criterion	2.340205
Sum squared resid	9.404678	Schwarz criterion	3.142423
Log likelihood	-27.80410	Hannan-Quinn criter.	2.630261
F-statistic	2.201269	Durbin-Watson stat	1.985873
Prob(F-statistic)	0.042530		

The residual behavior warrants the coefficient's reliability. The Jarque-Bera test for normality resulted in a 0.27 probability, which is not significant to reject the normality hypothesis. Likewise, the Q-statistic test, the Breusch-Godfrey Serial Correlation LM test results, for all variables and their lags, were not sufficient to reject the hypothesis of no serial correlation. Moreover, there is no sign of multicollinearity among the variables; and the model were stable and did not show any structural break. The summaries can be found in Appendix B, table B-20.

The Bound test results for long-run cointegration allow us to affirm that, at 5% of significance, the variables are jointly cointegrated. The Bound test summary is entirely available in appendix B, table B-20.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	5.294701	10%	3.17	4.14
k	2	5%	3.79	4.85
		2.5%	4.41	5.52
		1%	5.15	6.36
			Finite Sample:	
Actual Sample Size	40		n=40	
		10%	3.373	4.377
		5%	4.133	5.26
		1%	5.893	7.337

t-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-3.860465	10%	-2.57	-3.21
		5%	-2.86	-3.53
		2.5%	-3.13	-3.8
		1%	-3.43	-4.1

5.2. Thailand's Findings and Model Analysis.

For Thailand's analysis, the same set of variables used by Brazilians will be used as much as possible. The Augmented Dickey-Fuller (ADF) test for stationarity was applied to all variables as well as to their logarithmic-transformed form. The results were summarized in Appendix B, Table B-21. All variables and their log transformations are purely stationary – I(0) – or stationary integrated by 1 – I (1). Recall that this combination is suitable for ARDL methodology. Below is the table with the variables' abbreviations as they will appear in the statistical summaries.

Table 16 - *List of Abbreviations as in summaries.*

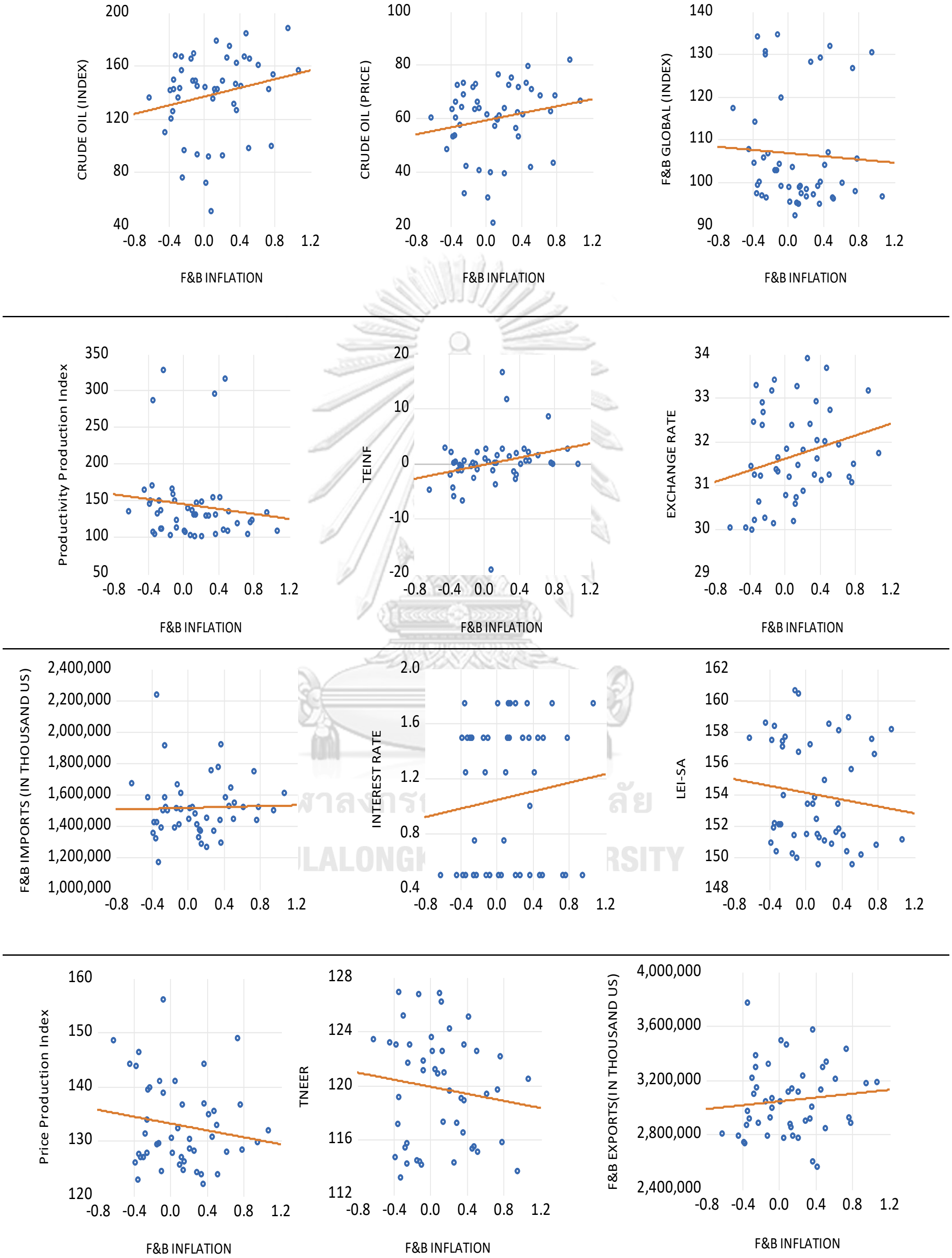
TF_BINF	THAI FOOD & BEVERAGE INFLATION (Dependent variable)
COI, DIFCOI	CRUDE OIL INDEX, First Difference of COI
LNCOI, DIFLNCOI	Log of COI, First Difference of Log COI
COP, DIFCOP	CRUDE OIL PRICE, First Difference of COP
LNCOP, DIFLNCOP	Log of COP, Fist Difference of Log of COP
GFI, DIFGFI	GLOBAL FOOD INDEX, First Difference of GFI
LNGFI, DIFLNGFI	Log of GFI, First Difference of Log of GFI
TAPI, DIFTAPI	THAI AGRICULTURAL PRICE INDEX, First Difference o TAPI
LNTAPI, DIFLNTAPI	Log of TAPI, First Difference of Log of TAPI
TAPROD, DIFTAPROD	THAI AGRICULTURAL PRODUCTION, First Difference of TAPROD
LNTAPROD, DIFLNTAPROD	Log of TAPROD, First Difference of Log TAPROD
TEINF, DIFTEINF	THAI ENERGY INFLATION, First Difference of Thai Energy Inflation
TFEXP, DIFTEXP	THAI FOOD EXPORTS, First Difference of TFEXP
LNTFEXP, DIFLNTFEXP	Log of TFEXP, First Difference of Log of TFEXP
TFIMP, DIFTFIMP	THAI FOOD IMPORTS, First Difference of TFIMP
LNTFIMP, DIFLNTFIMP	Log of TFIMP, First Difference of Log of TFIMP
TIR, DIFTIR	THAI INTEREST RATE, Fist Difference TIR
LNTIR, DIFLNTIR	Log of TIR, First Difference of Log of TIR
TLEI, DIFTLEI	THAI LEADING ECONOMIC INDEX, First Difference of TLEI
LNTLEI, DIFLNTLEI	Log of TLEI, First Difference of Log of TLEI
TNEER, DIFTNEER	THAI NOMINAL EFFECTIVE EXCHANGE RATE, First Difference of TNEER
LNTNEER, DIFLNTNEER	Log of TNEER, First Difference of log of TNEER

Before starting modeling, it is beneficial to check the correlation matrix in order to avoid aggregating highly correlated variables (degree of correlation larger than 0.7). The GFI variable, for example, displayed a high positive degree of correlation with TFIMP and TAPI. The result is unexpected for TFIMP (Imports) and can cause misleading interpretations. There might be an unobserved variable cointegrating DFI and TFIMP. TAPI and TLEI are positively correlated because economical heating can cause price pressure. Energy and crude oil are positively correlated, which is expected. TIR and TLEI are negatively correlated because a rise (decrease) in the latter implies a decline (rise) in the former. The whole matrix can be found in Table- B 23, appendix B.

After that, the dependent variable was plotted against the probable explanatory variables, as in Figure 10 below. The cost-push effect explains the positive relationship between food inflation and crude oil and energy prices. The agrarian production index and the agrarian price index are negatively associated with the variable of interest. The production correlation is expected; however, the production price should be positively correlated to inflation because of the pass-through mechanism from the production sector to retailers; thus, this latter relationship is non-sense and needs further investigation. The imports curve is relatively flat; in turn, the exports have a slightly positive inclination; the direct explanation is that the more exports, the less domestic food surplus.

Concerning monetary aspects, the positive relations between inflation and interest rate align with the theory: central banks must raise the interest rate to prevent inflation from spiraling out of control. Likewise, the exchange rate is well-known as a root fact of inflation. Lastly, NEER (nominal effective exchange rate) curve is negatively inclined once, according to the Bank of Thailand: an increase in NEER refers to the baht appreciation against Thailand's major trading partners and competitors. Then, holding everything else constant, the stronger the currency, the lower the inflation.

Figure 12 - *Scatterplot Food Inflation against explanatory variables.*



The next step consists of testing for Granger Causality to improve the chance of choosing meaningful regressors for the models. All variables were submitted to this test. Below, table 16 displays the statistically significant variables, at least at 10%. Bear in mind that the Granger Null Hypothesis is: Variable x does not Granger Cause variable Y. Thus, with the maximum lag of 4 months, only agricultural price and agricultural production and their transformed forms were able to reject the Null Hypothesis. On the other hand, accounting for the maximum of 8 months of lags, crude oil price and crude oil index allowed us to reject the Null Hypothesis. These results point out that oil prices and agricultural conditions can be worthy explanatory variables for food inflation.

Table 17 - *Thailand Granger Causality test*.

Pairwise Granger Causality Tests
Date: 10/17/22 Time: 13:57
Sample: 2018M01 2021M12
Lags: 4

Null Hypothesis:	Obs	F-Statist	Prob.
DIFTF_BINF does not Granger Cause DIFLNTAPI	43	1.77425	0.1568
DIFLNTAPI does not Granger Cause DIFTF_BINF		2.12518	0.0991
DIFTF_BINF does not Granger Cause DIFLNTAPROD	43	0.17444	0.9500
DIFLNTAPROD does not Granger Cause DIFTF_BINF		2.06362	0.1074
TF_BINF does not Granger Cause DIFTAPROD	43	0.68169	0.6095
DIFTAPROD does not Granger Cause TF_BINF		2.23621	0.0857
LNTAPI does not Granger Cause DIFTF_BINF	43	2.19138	0.0908
DIFTF_BINF does not Granger Cause LNTAPI		2.32193	0.0766
TAPI does not Granger Cause DIFTF_BINF	43	2.26609	0.0824
DIFTF_BINF does not Granger Cause TAPI		2.19458	0.0905

Table 17 - *Thailand Granger Causality test*.

Null Hypothesis	Obs	F-Statistic	Prob.
TF_BINF does not Granger Cause LNTAPI	44	2.54697	0.0566
LNTAPI does not Granger Cause TF_BINF		2.11538	0.0997
TF_BINF does not Granger Cause TAPI	44	2.40168	0.0684
TAPI does not Granger Cause TF_BINF		2.21752	0.0871

Pairwise Granger Causality Tests
Date: 10/17/22 Time: 14:17
Sample: 2018M01 2021M12
Lags: 8

Null Hypothesis:	Obs	F-Statist	Prob.
TF_BINF does not Granger Cause COI	40	0.42917	0.8914
COI does not Granger Cause TF_BINF		2.01960	0.0896
TF_BINF does not Granger Cause COP	40	0.45739	0.8731
COP does not Granger Cause TF_BINF		2.03040	0.0880

Finally, before presenting the model, we shall test for the breakpoint. The Chow test was applied for structural break; the F-statistic outcome was not enough to reject the following statement: there is no breakpoint in January 2020. Therefore, there is no need to use dummy variables.

Chow Breakpoint Test: 2020M01
Null Hypothesis: No breaks at specified breakpoints
Varying regressors: All equation variables
Equation Sample: 2018M01 2021M12

F-statistic	0.080735	Prob. F(1,46)	0.7776
Log likelihood ratio	0.084171	Prob. Chi-Square(1)	0.7717
Wald Statistic	0.080735	Prob. Chi-Square(1)	0.7763

Given the abovementioned guideline to avoid creating models Integrated by order 2 – I(2) or more, building models with moderated or highly correlated variables was modeled around 38 models. However, out of these models, 35 come out with very low adjusted R-squared (the percentage of the change in the dependent variable explained by the model minus the penalty for including useless variables), and low F-statistics. These models are available in Table b-30, appendix B.

Having said that, the models which passed by the criteria of significance, stability and reliability are:

- 1)$TF\_BINF = \delta_1 \Delta lnTAPROD_{t-4} + \delta_2 \Delta TENINF + \delta_3 \Delta TENINF_{t-2} + e_t$
- 2)$TF\_BNIF = \delta_0 + \delta_1 \Delta lnTAPI_{t-1} + \delta_2 \Delta TENINF + \delta_3 \Delta TENINF_{t-1} + \delta_4 \Delta TENINF_{t-2} + \delta_5 \Delta lnGFI + \delta_6 \Delta lnGFI_{t-2} + e_t$
- 3)$TF\_BNINF = \theta_1 TF\_BINF_{t-1} + \delta_1 \Delta lnTAPROD_{t-1} + \delta_2 \Delta TENINF + \delta_3 \Delta TENINF_{t-1} + \delta_4 \Delta TENINF_{t-2} + \delta_5 \Delta TENINF_{t-3} + \delta_6 \Delta TER_{t-1} + e_t$

5.2.1 Thailand's First Model

In the first model, three explanatory variables were initially attempted: Agricultural Production (log differences), Energy Inflation (first difference), and Nominal Effective Exchange Rate (log differences). However, the F-statistics did not have sufficient statistical significance, and the R-squared was too low – 0.2. Therefore, the NEER was changed by economic output proxy – LEI (log differences), which improved the r-squared to 0.27, as in table 17.

Regarding the coefficients, there was no statistical significance for the autoregressive part. The agriculture production, with four months of lags, is significant and the sign is as expected – negatively related to inflation since a rise in the quantity of supply causes a decrease in prices. For energy inflation, the contemporaneous coefficient and its three months lag are significant, and the positive sign is in line with the expectations. The LEI did not have any significance, although it improved the r-squared, without sacrificing stability.

Moreover, once all assumptions were observed, the residual diagnostics warrant that the coefficients have the least variance among all linear unbiased estimators. The error terms are normally distributed, and there is no sign of heteroscedasticity, auto-correlation, endogeneity, and multicollinearity. Besides, the model is stable with no structural break. The summary for all these tests is available in Appendix B, table B-23.

Table 18 - *Thailand Model 1. Short-run*

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/18/22 Time: 22:05
Sample (adjusted): 2018M06 2021M07
Included observations: 38 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTAPROD DIFLNTLEI, DIFTENINF
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 4, 0, 3)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.168132	0.164716	1.020737	0.3168
DIFLNTAPROD	-0.067020	0.187473	-0.357489	0.7236
DIFLNTAPROD(-1)	-0.351102	0.195159	-1.799055	0.0836
DIFLNTAPROD(-2)	-0.047853	0.202868	-0.235881	0.8154
DIFLNTAPROD(-3)	-0.213360	0.195864	-1.089331	0.2860
DIFLNTAPROD(-4)	-0.531583	0.187853	-2.829778	0.0089
DIFLNTLEI	-0.000225	0.000164	-1.372939	0.1815
DIFTENINF	0.022530	0.010126	2.225035	0.0350
DIFTENINF(-1)	0.009887	0.010602	0.932547	0.3596
DIFTENINF(-2)	0.028422	0.010153	2.799406	0.0095
DIFTENINF(-3)	0.018163	0.011115	1.634060	0.1143
C	165.8241	120.7410	1.373387	0.1814

Table 18 - *Thailand Model 1. Short-run*

R-squared	0.490954	Mean dependent var	0.082632
Adjusted R-squared	0.275588	S.D. dependent var	0.379920
S.E. of regression	0.323359	Akaike info criterion	0.831979
Sum squared resid	2.718579	Schwarz criterion	1.349112
Log likelihood	-3.807604	Hannan-Quinn criter.	1.015971
F-statistic	2.279630	Durbin-Watson stat	1.769332
Prob(F-statistic)	0.041197		

For the long-run analysis, the Bound test exhibits an F-statistics (8.59) expressively larger than the upper bound (6.61), enabling the rejection of the null hypothesis of non-cointegration in favor of the alternative hypothesis at any level of significance. The whole table for the bound test is displayed in table B-24.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	8.599887	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
Actual Sample Size	38	Finite Sample: n=40		
		10%	2.933	4.02
		5%	3.548	4.803
		1%	5.018	6.61

5.2.1 Thailand's Second Model

The second model contains the Agricultural Price Index (TAPI), the Energy Inflation (TENINF), and the Global Food Index (DFI). The agricultural price positively impacts inflation, considering one month lag. In turn, for this model, the energy affects the food inflation contemporaneously and with one and two months of lag. Both variables behave as expected; they move in the same direction as the dependent variable. However, the global food price had an unexpected path, negatively related to Thailand's food inflation. The adjusted R-squared was highly penalized by the number of lags. Nevertheless, the model is reliable and stable according to the residual diagnostics available in table B-26.

Table 19 - *Thailand. Model 2*

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/19/22 Time: 13:14
Sample (adjusted): 2018M06 2021M12
Included observations: 43 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTAPI DIFTENINF DIFLNGFI
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(2, 1, 4, 2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.247265	0.159701	1.548304	0.1320
TF_BINF(-2)	-0.292106	0.157012	-1.860401	0.0727
DIFLNTAPI	-1.496581	2.181460	-0.686046	0.4980
DIFLNTAPI(-1)	5.716617	2.234295	2.558577	0.0158
DIFTENINF	0.031928	0.011175	2.856976	0.0077
DIFTENINF(-1)	0.023168	0.011501	2.014368	0.0530
DIFTENINF(-2)	0.043758	0.013720	3.189281	0.0033
DIFTENINF(-3)	0.022768	0.012153	1.873490	0.0708
DIFTENINF(-4)	0.017830	0.011600	1.537071	0.1348
DIFLNGFI	-4.319051	1.957875	-2.205989	0.0352
DIFLNGFI(-1)	0.808867	2.036995	0.397088	0.6941
DIFLNGFI(-2)	-4.007452	1.979763	-2.024208	0.0519
C	0.138158	0.058888	2.346101	0.0258

R-squared	0.477022	Mean dependent var	0.103023
Adjusted R-squared	0.267831	S.D. dependent var	0.390711
S.E. of regression	0.334319	Akaike info criterion	0.891206
Sum squared resid	3.353076	Schwarz criterion	1.423662
Log likelihood	-6.160936	Hannan-Quinn criter.	1.087560
F-statistic	2.280317	Durbin-Watson stat	1.819147
Prob(F-statistic)	0.033226		

The Bound test for long-run cointegration reveals a long-term relationship among the variables within this model. The whole table is in appendix B, table B-27.

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	10.01040	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
			Finite Sample: n=45	
Actual Sample Size	43	10%	2.893	3.983
		5%	3.535	4.733
		1%	4.983	6.423
			Finite Sample: n=40	
		10%	2.933	4.02
		5%	3.548	4.803
		1%	5.018	6.61

5.2.3 Thailand's Third Model

Table 20 - *Thailand model 3. Short- run*

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/20/22 Time: 14:35
Sample (adjusted): 2018M05 2021M12
Included observations: 44 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTAPROD DIFTENINF DIFTER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 1, 3, 1)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.302778	0.137320	2.204911	0.0343
DIFLNTAPROD	-0.065121	0.170647	-0.381609	0.7051
DIFLNTAPROD(-1)	-0.362898	0.176551	-2.055482	0.0476
DIFTENINF	0.030326	0.009837	3.082690	0.0041
DIFTENINF(-1)	0.022944	0.009700	2.365480	0.0239
DIFTENINF(-2)	0.038198	0.010196	3.746214	0.0007
DIFTENINF(-3)	0.024698	0.009927	2.488117	0.0179
DIFTER	-0.139590	0.083312	-1.675501	0.1030
DIFTER(-1)	0.205765	0.085958	2.393781	0.0223
C	0.063049	0.052634	1.197879	0.2392

R-squared	0.450645	Mean dependent var	0.110909
Adjusted R-squared	0.305228	S.D. dependent var	0.389668
S.E. of regression	0.324800	Akaike info criterion	0.785501
Sum squared resid	3.586827	Schwarz criterion	1.190998
Log likelihood	-7.281017	Hannan-Quinn criter.	0.935879
F-statistic	3.098977	Durbin-Watson stat	1.978197
Prob(F-statistic)	0.007954		

The third model includes Agricultural Production (log differences), Energy inflation and Exchange Rate (first difference). The sign of all coefficients returned as expected. The regressive part was positive, meaning that the previous inflation affects the present inflation. The agricultural production variable had a negative sign and was statistically significant for one month of lag, which means that inflation tends to decrease when production rises. Energy inflation was positively significant for the contemporaneous result and for one, two and three months of lag. The one-month lag of the exchange rate was positively related to inflation; recalling that a rise in the exchange rate means depreciation, then an increase in the exchange rate tends to pull the inflation up.

Furthermore, model 3 seemed stable, according to the CUSUM test result. The coefficients are reliable, with error terms normally distributed (Jarque-Bera 0.59). Besides, we failed to reject the hypothesis of homoskedasticity, autocorrelation, and multicollinearity, as shown by Table B-28, Appendix B.

For the long-run relationship, the variables are cointegrated and tend to return to long-term equilibrium in case of disturbance. The F-statistics for the Bound test was 12.79, far higher than the upper bound for any level of significance. The entirely Bound test result for cointegration is available in tables B-29. An excerpt of this test is below.

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	12.79867	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
			Finite Sample: n=45	
Actual Sample Size	44			
		10%	2.893	3.983
		5%	3.535	4.733
		1%	4.983	6.423
			Finite Sample: n=40	
		10%	2.933	4.02
		5%	3.548	4.803
		1%	5.018	6.61

5.3 Discussion

In this section, the results from sections 5.1 and 5.2 will be discussed, contrasted, and compared. The models designed in the mentioned sections were built in two formats: level-Log and level-Log Difference. Given that, the interpretation will be based on the following definition:

- Linear – Log
  $y_t = \beta_1 + \beta_2 \ln x_t + e_t$
  $\beta_2 = \frac{\Delta Yt}{\Delta \ln Xt} \xrightarrow{yields} \frac{dy}{dx} = \frac{\beta 2}{x} \xrightarrow{yields} dy = \frac{\beta 2}{x} . x \xrightarrow{yields} \Delta Y = \frac{\beta 2}{100}$ (everything else held constant)

- Linear-log Difference

$\Delta Y = \text{Log}(x_t) - \log(x_{t-1}) \cong \frac{Yt - Yt-1}{Yt-1}$, when the number is small; otherwise, the logarithm will be calculated.

Out of 13 possible explanatory variables, along with their transformed forms, only 6 had explanatory power: Agricultural Production, Agricultural Price, Energy Inflation, Global Food Index, Nominal Effective Exchange Rate, and Exchange Rate. These variables, encompassed by the three models proposed in sections 5.1 and 5.2, will be thoroughly analyzed in the following sections.

5.3.1Thailand's and Brazil's Model 1.

- $BF\_BINF = 1.05 + 0.62 BF\_BINF_{t-1} - 52.95 \Delta \ln BAPROD_{t-6} + e_t$
- $TF\_BINF = -0.53 \Delta \ln TAPROD_{t-4} + 0.02 \Delta TENINF + 0.02 \Delta TENINF_{t-2} + e_t$

For Brazil's First Model, the natural logarithm of 52.95 is approximately 3.97; the negative sign means that the dependent variable moves in an oppositive way from the independent variable. For each one percent increase in production growth, there is a reduction of 3.87 units of inflation, everything else holding constant, with six months of lag. The reverse is also true; for each one percent decrease in production growth, there is an increase of 3. 97 units in food inflation. In this model, the intercept and the regressive part are different from zero for Brazil. These non-null coefficients indicate i) a degree of inflation stickiness and ii) that the expectations are backward looking (adaptative); in order words, the firms, households, and workers expect that the subsequent inflation will be similar to the current one. Thus, the economic agents act accordingly: bearing in mind that the prices will rise anyway, the workers ask for a rise in wages, and the firms set the prices based on the level the past inflation. Moreover, the Interest rates did not show statistical relevance; besides, because this variable is stationary only at level, it was not possible to perform any transformation.

Brazil is known as one of the most prominent food producers; nevertheless, according to the Center of Advanced Studies in Applied Economics (CEPEA), grain production grew only 4.3% in 2020 (below the average of the previous ten years - 7.7%). Moreover, fruits and vegetables had a slight decline in production. During the pandemic, Brazil experienced a reduction in the production of rice, beans, coffee beans, cassava, potato, orange, cocoa, grape, apple, banana, and papaya (Pereira & Castro, 2022). According to IPEA (2020, b), rice production stagnated. Moreover, according to BACCARIN & OLIVEIRA (2020), the Brazilian production of non-tradable products is tightly related to domestic demand, so the consumers have little bargaining power. In addition, during the Covid-19 pandemic, consumers increased the quantity per purchase to stockpile non-perishable products, such as rice and beans. Therefore, we can highlight that, in Brazil, there is no expressive surplus of eatable agricultural production. Thus, any disturbance can encourage wholesalers and producers to raise the prices, and this increase is easily passed through to retailers until they reach the final consumers.

For Thailand, one percent of the decrease in the growth of agricultural production can lead to a reduction of 0.53 units in food inflation, with four months of lag. This rate is far lower than Brazil's transmission rate. A small magnitude of the food production coefficient explains why the decline in production did not spill over to the retailer sector. In the first quarter of 2020, the Agricultural Producer Index contracted by 6%, especially because of the droughts. In the first semester of 2020, the water reservoir was at its lowest level. In general, the 2020 agricultural production decreased by 3.4 %. The water scarcity during the first semester can partially explain the food price pick in the third quarter of 2020.

On the other hand, an increase in rural unemployment contributed to reducing the pressure for wage rises, which, in turn, lessened production costs. Another fact that might have contributed to the decrease in prices is the decline in rice and fishery exports. Nevertheless, in the third quarter of 2020, production and rural unemployment started to stabilize, and some products, like fruits and poultry, even increased their production. In 2021, weather conditions changed, and the water supply was enough to boost the crops. The third quarter of 2021 was marked by an expressive increase in production – around 8%. However, it was insufficient to contain an inflation peak in the fourth quarter.

Thailand's first model is also composed of the energy element, which is understood as domestic removable and non-removable energy sources. Thailand's Model 1 indicates that one unit of increase in energy inflation growth adds 0.02 units in food inflation contemporaneously and after two months of lag. Mathematically: ΔTF&BInflation = 0.2 ($TENINF_t$ – $TENINF_{t-1}$) + 0.2 ($TENINF_{t-5}$ – $TENINF_{t-4}$). Since Food Inflation = %Δ in food CPI, and Energy Inflation is the %Δ in energy CPI, 0.2 is the elasticity of Food CPI against the Growth of Energy CPI. Therefore, a negative change in energy CPI leads to a negative impact on food inflation. Although the monthly energy inflation has had a volatile behavior, the accumulated rate for the first three semesters of 2020 decreased by 10%. It is possible to infer that keeping the change in energy prices under zero greatly contributed to negative food inflation during Q.4 of 2020 and Q.1 of 2021. The energy prices only reached the level of January 2020 in April 2021, which had an increase of 8% from April to December 2021. It is important to stress that the Thai Model has neither an intercept nor an autoregressive part. With this result, one can infer that the expectation is forward-looking (rational); the current rate is independent from the previous ones.

5.3.2 Brazil’s and Thailand’s Model 2

- a) $BF\_BNIF = 0.3BF\_BINF_{t-1} + 13.76\Delta lnBAPI_{t-1} + 0.09BENINF_{t-1} + e_t$
- b) $BF\_BNINF = 0.42 + 17.42\Delta lnBAPI_{t-1} + 0.12\Delta BENINF_{t-1} + e_t$
- $TF\_BNIF = 0.13 + 5.71\Delta lnTAPI_{t-1} + 0.03\Delta TENINF + 0.023\Delta TENINF_{t-1} + 0.043\Delta TENINF_{t-2} - 4.31\Delta lnGFI - 4\Delta lnGFI_{t-2} + e_t$

Brazil's model 2 was split into two: model "a" is formed by the autoregressive part, the Brazilian Agricultural Price Index (BAPI), and the Brazilian Energy Inflation (BENINF); whereas model "b" is formed by the intercept, Agricultural Price Index and Energy Inflation. Regarding model "a," each unit change in last month's food inflation add 0.3 units to the current one. Concerning energy inflation, according to model "a," each one unit of positive change in BENINF adds 0.09 units in food inflation one month after. For model "b," each unit of positive energy inflation changes leads to an increment of 0.12 units in food inflation after one month. With respect to BAPI, each positive change in the Agricultural Price Index growth leads to an addition of 2.62 (Ln 13.76) units in food inflation; in turn, in model "b," each percentage change in the BAPI growth adds 2.85(Ln 17.42) units to food inflation.

The energy inflation – renewable and non-renewable sources – was under control until the Q.3 of 2020, when it started to accelerate, reaching 8.2% in Q.4. This index slowed down during Q.1 of 2021; however, from Q.2 onwards, it grew in a rapid pace: 6.7% in Q.2, 14.68% in Q.3 and, 3.78% in Q.4. For the Brazilian model, the gap between the rise in energy and its reverberation in food inflation takes only one month. These figures align with food inflation peaks: in Q.3 and Q4. of 2020 and Q.3 of 2021.

The Agricultural Price Index (API) is understood as the selling price received by domestic producers for their output and is heavily affected by demand and costs. The Brazilian Agricultural Price index has a sharp increase of 13.1% in Q.1 of 2020, mainly due to grain prices growing rampant. In this period, the demand-pull transmission mechanism was also verified. At the beginning of the pandemic, consumers stockpiled non-perishable food, such as rice and beans, which raised the retailer's demand towards wholesalers at a level over what had been expected. According to IPEA (2020, b), the production cost was inflated mostly by the administrated prices and input costs. For instance, in Brazil, paddy crops rely on electric irrigation, and other crops depend highly on imported fertilizers, which have become more expensive due to currency depreciation. Besides, for the first semester, the cost of production for grains was over two standard deviations from what was expected (Cepea, 2020). In Q.3 and Q.4 of 2020, BAPI rose more than 5 and 11%. The grains' production cost was the main culprit. These sequential rises stopped in Q.1, Q.2, and Q.3 of 2021 when the costs cooled off.

Thailand's second model counts on intercept, Agricultural Price Index (TAPI), Energy Inflation (TENINF) Growth, and Global Food Index (GFI) Growth. The intercept means that, in this model, if there were no other variables, the inflation would be 0.13%. Regarding TAPI, the rise in agrarian prices takes one month to affect food inflation. According to this equation, each one percent increase in the growth of agricultural prices leads to a rise of approximately 1.74 (Ln 5.71) units in food inflation one month after the increment. The Global Food Index displayed an unexpected negative relationship with Thailand's food inflation. Each positive percentage change in GFI growth leads to a decrease of 1.43 (ln 4.31) units in current food inflation and 1.38 (ln 4) after two months. This relationship is unexpected; however, indeed, the lowest level of Thai food inflation – Q4/2002 and Q1/2021 - converge with the Global Food Index hike. Instead, a positive and strong relationship between GFI and TAPI was identified, as depicted in Table 21, a. In the Granger Causality test below, the F-statistics allows for rejecting the Null hypothesis. In any case, it was preferable to keep the GFI in the model because its permanence enhances the Adjusted R-squared and the Jarque-Bera test for normality. Besides, this model's Variance Inflator Factor was below the acceptable level, as shown in section 5.2.2, and there is only a weak correlation between the contemporaneous $DIFLNTAPI_t$ and $DIFLNDFI_t$ variables, as displayed in Table 21,b.

Table 21 - *GFI and TAPI Granger Causality and Correlogram Tests*

a)Granger Causality

Pairwise Granger Causality Tests
Date: 10/28/22 Time: 14:17
Sample: 2018M01 2021M12
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
DIFLNTAPI does not Granger Cause DIFLNGFI	43	0.58382	0.6765
DIFLNGFI does not Granger Cause DIFLNTAPI		3.10851	0.0278

b) Correlogram

	DIFLNTAPI	DIFLNGFI
DIFLNTAPI	1.000000	0.148761
DIFLNGFI	0.148761	1.000000

The Thai Energy Inflation was discussed in section 5.3.1; having said that, we shall discuss Thailand's Agricultural Price Index. This index soared during the pandemic period. For example, TAPI recorded 8.8% in Q.1 of 2020; however, the raises were concentrated in non-eatable products such as rubber. Conversely, the raisings registered in Q.3/2020 (6.4%) and Q.4/2020 (11%) were more expressive in eatable products - poultry and palm oil. For the main staple – rice – TAPI contracted continuously until Q3/2021. TAPI had steady growth for the first semester of 2021, receding only after Q3/2021.

Despite the persistent and expressive surge in TAPI, food inflation in Thailand was kept under control due to the low pass-through rate - each one percent of positive change in TAPI adds 1,73 units in inflation. For example, the Growth TAPI in

September 2021 was 0.002890; thus, the expected increase in food inflation one month ahead will be 0.005 units.

5.3.3 Brazil's and Thailand's Model 3

- $BF\_BNINF = 0.67BF\_BINF_{t-1} + 0.14BENINF_{t-1} + 0.12BENINF_{t-7} + 8.94\Delta lnBNEER_{t-7} + e_t$

- $TF\_BNINF = 0.3TF\_BINF_{t-1} - 0.36\Delta lnTAPROD_{t-1} + 0.03\Delta TENINF + 0.02\Delta TENINF_{t-1} + 0.03\Delta TENINF_{t-2} + 0.02\Delta TENINF_{t-3} + 0.2\Delta TER_{t-1} + e_t$

Model 3, for both countries, encloses variables that account for energy inflation, food production, and monetary stance. Normally, the specialized literature suggests the Nominal Effective Exchange Rate (NEER) as the adequate monetary predictor of food inflation; nevertheless, for Thailand's model, the former variable did not show statistical significance. The Exchange Rate was used instead. Moreover, since energy inflation and agricultural production have already been comprehensively discussed, this section will focus on the monetary variables.

The autoregressive coefficient of the Brazilian model has twice the magnitude of its equivalent in Thailand's model. In Brazil's model, each unit change of the previous inflation adds 0.67 units to the current one. Regarding energy inflation, each unit of positive change adds 0.14 and 0.12 to food inflation with one and seven months of lags, respectively.

In the Brazilian model, concerning the monetary stance, one percent positive change in BNEER growth adds 2.19 (ln 8.98) units in food inflation. NEER is defined as the measure of the value of a currency against a weighted average of several foreign currencies. Contrarily to other countries, an increase in the Brazilian NEER indicates a depreciation of the local currency against the weighted basket of its trading partners. In other words, an increase in Brazil's NEER index means more Brazilian Reais (R$) are needed to buy the same currency basket. From January 2020 to December 2021, the BNEER depreciated by 31.50%. The most prominent devaluation occurred in Q1/2020 – 15%, and the highest peak of Brazilian food inflation for the pandemic period occurred during Q.4/2020; this is consistent with the model, which forecasted that the impact of NEER devaluation occurs around seven months later, as can be seen in Figure 2, Chapter 01.

In Thailand's model, each unit of the previous inflation adds 0.3 units to the current one. Moreover, each percentage positive (negative) change in agricultural production growth reduces (increases) 0.36 units in food inflation after one month. Besides, each one-unit change in Energy Inflation Growth also changes, in the same direction, the current food inflation and the one and two-months ahead food inflation by 0.03, 0.02, and 0.03 units, respectively.

The Thai Baht started the pandemic period stable with slight appreciation during the entire year of 2020. According to the third model, the impact of currency change on food inflation occurs one month later. The highest appreciation occurred in Q.4/2020, which matches the sustained negative food inflation period - from October 2020 to March 2021. Figure 02 from Chapter 01 portrays the congruity between the downward part of the food inflation curve and the periods of Thai Bath appreciation: 1.93% in Q3/2020, 2.25% in Q.4/2020, and 1.07% in Q.1/2021. Likewise, the upward part of the food inflation curve is concurrent with the depreciation periods: 2.11% in Q2/2020, 3.53% in Q.2/2021, 2.99% in Q.3/2021, and 1.37% in Q.4/2021.

In sum, after the three models have been analyzed, we can conclude that the findings are in line with KWON and KOO (2009), concerning the importance of the Producer Price Index (here treated as the Agricultural Price Index) and the cost-push characteristics. The results agreed with GONGSIANG & AMATYAKUL's (2020), regarding world food price significance. However, this study is partially in agreement with IDDRIZU (2021). The importance of the exchange rate to food inflation was recognized, but the interest rate was not significant.

5.4 Research Question Analysis and Final Considerations

In our mission to explain the reason that gave rise to the food inflation hike in Brazil during the Pandemic (2020-2021) while Thailand experienced low and stable food inflation, 14 key economic variables were analyzed. Nevertheless, some of them did not show any statistical significance; for Brazil: Interest Rate, Crude Oil Price, Crude Oil Index, Global Food Index, IBC_BR, Food Import, Food Export, and Exchange Rate. Thailand's non-relevant variables converged with Brazil's, except for the Global Food Index, which indicated an unexpected result, and for the Nominal Effective Exchange Rate, which is meaningless to Thailand but not to Brazil.

The analysis of this chapter's previous sections gave elements to answer one of the questions from which this study stemmed: What are the drivers of F&B inflation? Are they different in Brazil and Thailand? The answer to these inquiries can be found in models 1, 2, and 3. For Brazil, the variables which demonstrated predictive power were: Domestic Energy Inflation (BENINF), Agricultural Production Index (BAPROD), Agricultural Price Index (BAPI), and the Nominal Effective Exchange Rate (BNEER). For Thailand, the variables with explanatory power were: Domestic Energy Inflation (BENINF), Agricultural Production Index (TAPROD), Agricultural Price Index (TAPI), and the Exchange Rate (TER). Therefore, the critical variables explaining food inflation during Covid-19 were mainly the same for Thailand and Brazil, except for the monetary stance.

Recalling that a provisional answer was proposed to solve the Research Question, the solution was materialized in the form of these two hypotheses below:

H_0 : Domestic Energy Inflation has no impact on Food and Beverage Inflation.
H_1: Domestic Energy Inflation has an impact on Food and Beverage Inflation.

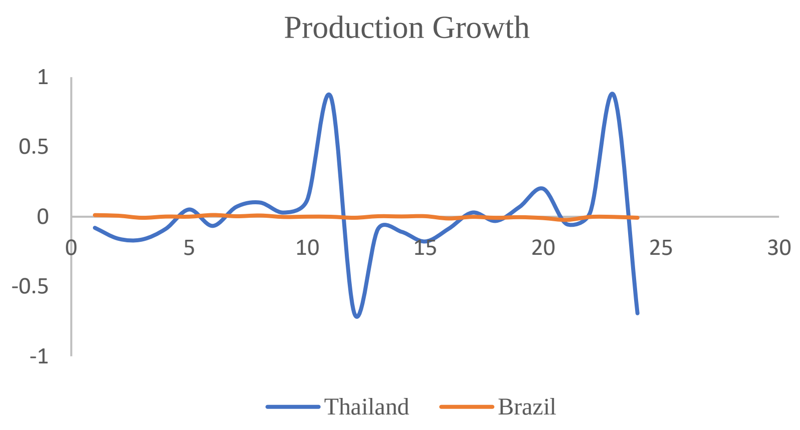
H_0 : There is no relationship between the Interest Rate and Food and Beverage Inflation.
H_1: There is a relationship between the Interest Rate and Food and Beverage Inflation.

For the first hypothesis, for both economies, the models presented allow for rejecting the null hypothesis in favor of the alternative. For the second hypothesis, there was no evidence to reject the null hypothesis.

Another part of the research question, and its major issue, is: Why could Thailand control F&B inflation while Brazilian inflation was high and above the target? The coefficients of the predictor variables can answer this question.

The Agrarian Production Growth variable coefficient for Thailand (-0.53) is almost 8 times smaller than Brazil's (-3.97). However, as previously explained, Brazil's production of non-tradable and eatable products is quite tight during the Pandemic. When the production's variation is positive (negative), the food inflation tends to decrease (increase). Figure 13 below displays that Brazil's production growth was relatively stable; however, this index refers to the production of all kinds of crops. Nevertheless, as stated in sections 1.1 and 5.3.1, Brazilian production growth for fruits, rice and beans was unstable and, not seldom, negative. This negative production growth turns the coefficient positive, increasing inflation. Given the heterogeneity characteristics of production for tradable and non-tradable products, future research can improve this study by segregating the data for the main staples in each economy and then having a more accurate estimator for the role of production growth in curbing food inflation.

Figure 13 - *Production Growth*



Note. The values were calculated by taking the log difference of the Production Index. The raw data is available in Appendix A.

Energy inflation is another crucial driver of food inflation. For the Brazilian model, this variable was regressed using two formats: at level and first difference; for Thailand, only the former was used. Therefore, for the variable at level, its impact on the Thai and Brazilian economies cannot be directly compared.

According to Brazilian Model 2a, the energy influence (at level) is quick and robust. Each unit change in energy inflation leads to a 0.09 increase in food inflation, with one month of lag. For example, in November 2020, the Brazilian energy inflation was 0.32% and jumped to 7.64%, a change of 7.32 units. This increment adds an expected positive change of 0.65 units in the food inflation of January 2021. In this case, the word unit is interchangeable with percentage because both variables are in percentage form.

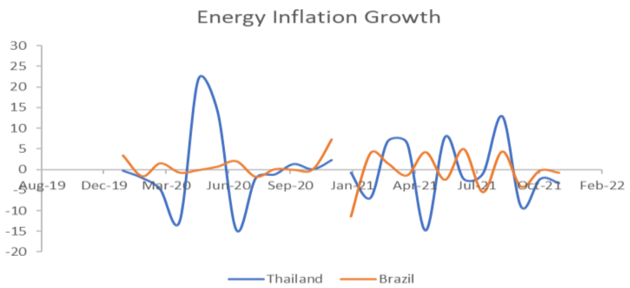
Regarding the Growth in Energy Inflation Growth (First Difference), for Brazil, Model 2b reveals that each unit positive change in this coefficient leads to an increase of 0.12 units in the subsequent food inflation. For Thailand, the impact is similar to Brazil, but it is spread throughout the months.

This finding is in line with the literature. Energy, electricity, gas, and oil are crucial inputs for food production throughout the entire production chain – "farm to fork." In Brazil, for example, many crops rely on electricity to maintain their irrigation system. About 30% of global energy is consumed in the agricultural and food sector. According to the DAY (2011), agri-food supply heavily depends on fossil fuel inputs –both direct and indirect. Moreover, both economies have a well-developed food industry, which is highly energy-consuming throughout each stage, such as cleaning, brewing, preparing, packing, and transportation.

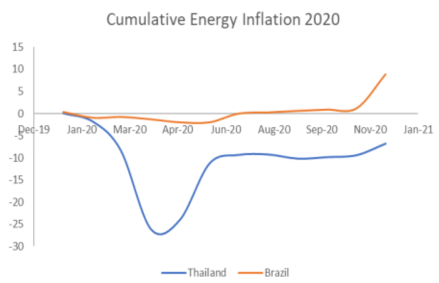
Thailand’s policy of keeping the cumulative energy inflation low was crucial to offset other inflationary pressures. On the other hand, Brazil did not take advantage of the slump in international crude oil prices in 2020 to promote a more aggressive reduction in domestic energy prices (Figure 14).

Figure 14 - *Energy Inflation*

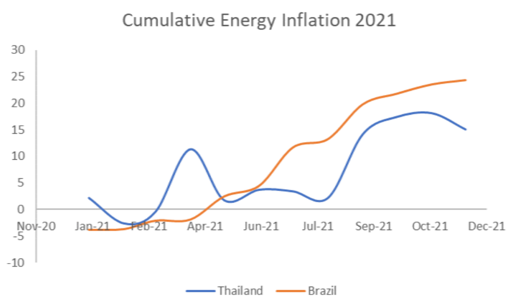
a)



b)



c)



Note. The raw data can be found in Appendix A.

The Agricultural Price Index (API) Growth exhibited relevant outcomes for both economies. This macroeconomic key variable is addressed by Model 2. For the Brazilian case, this model was split into two: one equation contains the autoregressive component, and the other contains the intercept, but the coefficient is virtually the same. We shall analyze the latter due to its similarity with Thailand’s Model 2. The

Thai Agricultural Price Index (TAPI) Growth was in the order of 1.72, whereas Brazil’s (BAPI) Growth was 2.85 – more than 65% higher.

During the Covid-19 Pandemic, Brazil and Thailand faced a surge in API. In Brazil, the inputs became extremely costly because most of them are imported, such as fertilizers, whose prices are highly impacted by currency depreciation and by crude oil international prices. Similarly, Thailand’s agrarian production costs soared during the Pandemic, among other reasons, because of the acute drought that lasted all through the year 2020. The API growth for both countries was similar (see Figure 15). On average, outliers excluded, TAPI monthly growth was 0.005%, slightly smaller than Brazil’s – 0.0065%. Therefore, the critical point here is the transmission rate. BAPI transfer to Brazilian food inflation is more than 65% higher than what is transmitted by TAPI to Thailand’s food inflation. A necessary conclusion is that food prices are more amplified throughout the food supply chain in Brazil than in Thailand.

Figure 15 - *Agricultural Price Index Growth*

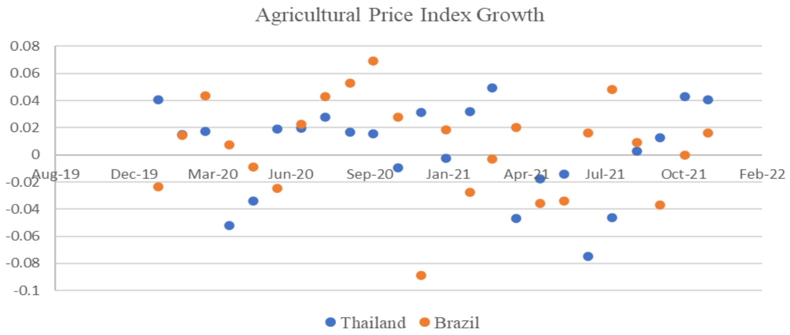
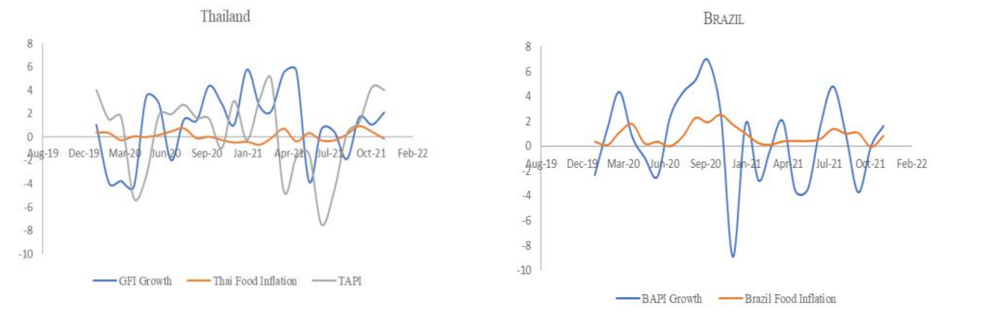


Figure 15 - *Agricultural Price Index Growth*



Note. The average Agricultural Price Index Grow – Thailand: 0.003539, Brazil: 0.005208.
The trimmed average (excluded outliers) – Thailand: 0.0050, Brazil: 0.0065
The raw data can be found in Appendix A.

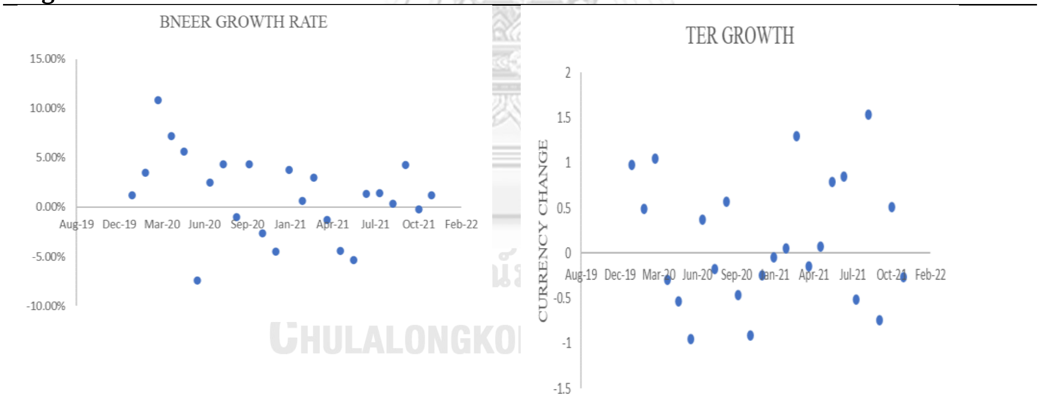
The relation between Global Food Index Growth and Brazilian Food Inflation did not depict statistical reliability. Besides, the negative relationship between GFI growth and Thai Food Inflation is awkward and needs further investigation by future researchers.

Finally, regarding the monetary stance, while NEER has suited the Brazilian model, Exchange Rate fits better than the Thai model. Thus, there is an obstacle to the direct comparison between the two equations. TER is the value of the Thai Bath against the US Dollar, and BNEER is the value of the Real against a currency basket of Brazil's main trade partners. Nevertheless, a valid comparison is how quickly the regressor impacts the variable of interest. For example, whereas BNEER takes 7 months to reach the Brazilian Food Inflation, TER takes only one month.

While the Brazilian Exchange Rate depreciated around 30%, TER remained quite steady. Figure 16 shows BNEER changes represented in percentage, and TER represented in units of currency. Recalling that, in the Figure 16, when the dot is below zero, it means currency appreciation, and when above zero it means currency depreciation.

According to Thai Model 3, each unit change in the TER's growth adds 0.2 units to food inflation. However, the TER net growth during this period was only 2.28 units; therefore, the net increment that food inflation suffered due to Thai depreciation was less than half percent. As for Brazil, the BNEER coefficient was expressive in size. Each percentage change in BNEER's growth rate led to 2.19 units change in food inflation. Another important distinction between the two economies is that the Brazilian currency's impact takes longer than in Thailand. This might be because Brazilian agricultural imports are concentrated in inputs, such as fertilizers. In other words, currency depreciation mainly affects the beginning of the Brazilian production chain. Thus, the rises take a while to reach final consumers.

Figure 16 - *BNEER Growth Rates and TER Growth*



Note The raw data can be found in Appendix A.

In sum, many reasons contributed to Thailand keeping its food inflation low and stable during the Pandemic. First, enough production of the leading food staples, rice (especially in 2021) and fruits, whereas the Brazilian production of eatable and non-tradable agrarian products stagnated. Second, the low transmission rate of the Agricultural Price Index to the final consumers. Third, the low level of energy inflation during most of this period. Last, the control and stability of the Exchange Rate.

Chapter 06

CONCLUSION

This Chapter will conclude this study by abridging the main research findings in relation to the research question. It will also review the constraints of the study and spot opportunities for future research.

In recent years, Thailand and Brazil have had remarkable net export performance in agrarian products. Moreover, both economies count on a well-developed food industry. During the two years of the acute phase of the COVID-19 Pandemic, global food prices had increased persistently. Both countries were assumed to have the tools to protect their economies from rampant food inflation. However, during the analyzed period, food prices in Brazil started escalating, whereas, in Thailand, they remained low and stable. This fact raises questions about why Brazil could not control food price hikes.

Based on the literature review, this study selected 13 macroeconomic variables that could provide elements to help explain food inflation behavior: Agricultural Price Index, Agricultural Production Index, Domestic Energy Inflation, Crude Oil Price, Crude Oil Index, Global Food Price Index, Food Exports, Food Imports, Proxy for monthly DGP (one for each country), Exchange Rate, Nominal Effective Exchange Rate, and Interest Rate. However, out of these variables, only 5 displayed meaningful statistical significance: Agricultural Price Index, Agricultural Product Index, Domestic Energy Inflation, Exchange Rate, and Effective Exchange Rate. These variables were analyzed by applying the Autoregressive Distributed Lag methodology. Three models were built, using, as much as possible, the same set of variables for both countries to compare these two economies.

Unfortunately, Romer's hypothesis of a negative correlation between inflation and the degree of openness could not be empirically investigated. This limitation is because Thailand's monthly GDP is unavailable, and the number of observations provided by the quarterly GDP is insufficient to conduct reliable statistics. However, two components of the Degree of Openness index (imports and exports) and one proxy for monthly GDP (Thailand's LEI and Brazil's IBC_BR) were evaluated, and none of them demonstrated statistical relevance to food inflation during the analyzed period. Nevertheless, Thailand's and Brazil's graphs of the Degree of Openness against food inflation depicted some delayed positive relationship between those two variables in some fragments of the studied period, contrary to which states Romer's hypothesis.

The Brazilian Agrarian Production Index has been shown to be highly influential in curbing inflation, even more than in Thailand; however, because the agricultural production in the years comprised by this study (2020-21) was tightly related to the demand, there was no space for this possibility to be seen in practice. Brazilian production growth of the main food staples (rice, beans, fruits, and vegetables) and non-tradable products stagnated. Based on the study presented here, we can state that, in Thailand, the elasticity of the Agrarian Production Index related to the Food Price Index is weaker than in Brazil. Nonetheless, because of the excellent weather conditions in 2021, Thailand's Production Growth warranted enough supply of staple foods. This surplus fostered the conditions to cool off any inflationary pressure in Thailand until the end of 2021. Not unlike Brazil's Agricultural Price Index, Thailand's soared. However, the API's pass-through was smaller in the latter than in the former country. Therefore, the best evidence suggests that Thailand's food chain (farm to fork) is more price-efficient than Brazil's during the Pandemic period.

Regarding the rate at which domestic energy inflation impacts food prices, both countries had the same magnitude; however, it was more concentrated in Brazil. Generally, it took only one month for the variation in energy inflation to reach food inflation in Brazil, whereas, for Thailand, the exact impact was diluted over three months. Moreover, on average, Thailand kept the domestic energy price at a low level, which was critical to controlling food prices.

Finally, related to the monetary stance, the Thai Baht remained stable during the Pandemic, whereas the Brazilian Real depreciated by 30%. Due to statistical constraints, Brazil's food inflation had the Nominal Effective Exchange Rate (NEER) as the monetary explanatory variable, and Thailand had the Exchange Rate (ER). In Brazil, the transmission rate of each percentage change in NEER was huge in magnitude, around 2.19 units of inflation. Besides having had lower currency depreciation (about 7%), Thailand's degree of transmission from the Exchange Rate to food inflation was low (0.2 units per unit of Thai Bath change).

Monitoring food inflation is extremely relevant in low-income and developing countries because food encompasses a massive percentage of the consumption basket in those countries. In emerging economies, the Food price increase can condemn people to starvation. This study spotted the main macroeconomic elements which conducted food prices to soar in Brazil during the Pandemic.

The main limitation of this study was the scarcity in the literature about food inflation during the Covid-19 Pandemic. Many facts contributed to this lack of studies. First, in the past few years, the world has experienced a sustained period of low inflation; therefore, there was no motivation to investigate this issue. Second, food inflation used to be a low-income country problem, and in these countries, the production of specialized publications is quantitatively lower than in developed centers. Finally, the Pandemic occurred recently; peer-reviewed and published scientific work, though, takes time.

Some issues could be more deeply investigated – for example, why commodities prices were negatively correlated to Thailand's food inflation. Besides, contrarily to what has been pointed out by many scholars, the interest rate was statistically unlike to be a good predictor of food inflation, and this needs additional analysis. Moreover, future research can contribute to the field by analyzing food production in each category and figuring out whether there is a group in which production growth is more efficient in curbing inflationary pressures.

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APPENDIX A

Raw Data

Table A- 1

Food and Beverage Inflation 2018 - 2019

	MONTHLY INFLATION (MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2018	-0.10%	0.74%	-0.10%	0.74%
FEB/2018	-0.39%	-0.33%	-0.49%	0.41%
MAR/2018	-0.28%	-0.07%	-0.77%	0.34%
APR/2018	0.78%	0.09%	0.01%	0.43%
MAY/2018	0.45%	0.32%	0.46%	0.75%
JUN/2018	-0.15%	2.03%	0.31%	2.79%
JUL/2018	-0.33%	-0.12%	-0.03%	2.67%
AGO/2018	0.51%	-0.44%	0.48%	2.22%
SEP/2018	0.28%	0.15%	0.77%	2.37%
OUT/2018	0.14%	0.59%	0.91%	2.98%
NOV/2018	0.35%	0.39%	1.26%	3.38%
DEZ/2018	-0.36%	0.44%	0.90%	3.83%
JAN/2019	0.33%	0.90%	0.33%	0.90%
FEB/2019	0.15%	0.78%	0.48%	1.69%
MAR/2019	0.20%	1.37%	0.68%	3.08%
APR/2019	0.61%	0.63%	1.30%	3.73%
MAY/2019	1.07%	-0.56%	2.38%	3.15%
JUN/2019	0.13%	-0.25%	2.51%	2.89%
JUL/2029	0.01%	0.01%	2.19%	2.90%

Food and Beverage Inflation 2018 - 2019

	MONTHLY INFLATION (MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
AGO/2019	-0.30%	-0.35%	2.22%	2.54%
SEP/2018	0.12%	-0.43%	2.34%	2.10%
OCT/2019	0.10%	0.05%	2.44%	2.15%
NOV/2019	-0.35%	0.72%	2.08%	2.89%
DEZ/2019	-0.13%	3.38%	1.95%	6.36%

Note: a) Thailand's monthly data was extracted from the Bureau of Trade and Economic Indices – Minister of Commerce. Retrieved from: http://www.price.moc.go.th/
b) Brazilian's data was extracted from Central Bank of Brazil – BACEN, Time-Series dataset, IPCA – Food and Beverage, Cod. 1635. Retrieved from: https://www3.bcb.gov.br/sgspub/consultarvalores/consultarValoresSeries.do?method=consultarValores.
c) With the updating of the weighting ponderation, obtained by the Household Budget Survey – POF – were ameliorated the component of IPCA from January 2020 onwards.

Table A- 2

Food and Beverage Inflation – 2020 - 2021

	MONTHLY INFLATION (MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
Jan-20	0.41%	0.39%	0.41%	0.39%
Feb-20	0.36%	0.11%	0.77%	0.50%
Mar-20	-0.25%	1.13%	0.52%	1.64%
Apr-20	0.08%	1.79%	0.60%	3.46%
May-20	0.02%	0.24%	0.62%	3.70%
Jun-20	0.2%	0.38%	0.82%	4.10%
Jul-20	0.5%	0.01%	1.33%	4.11%
Aug-20	0.76%	0.78%	2.10%	4.92%
Sep-20	-0.08%	2.28%	2.01%	7.31%

Food and Beverage Inflation – 2020 - 2021

MONTHLY INFLATION (MoM)			ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
Oct-20	0.05%	1.93%	2.06%	9.38%
Nov-20	-0.23%	2.54%	1.83%	12.16%
Dec-20	-0.45%	1.74%	1.37%	14.11%
Jan-21	-0.38%	1.02%	-0.38%	1.02%
Feb-21	-0.63%	0.27%	-1.01%	1.29%
Mar-21	-0.08%	0.13%	-1.09%	1.42%
Apr-21	0.73%	0.4%	-0.36%	1.83%
May-21	-0.35%	0.44%	-0.71%	2.28%
Jun-21	0.36%	0.43%	-0.36%	2.72%
Jul-21	-0.26%	0.6%	-0.62%	3.33%
Aug-21	-0.26%	1.39%	-0.87%	4.77%
Sep-21	0.25%	1.02%	-0.63%	5.84%
Oct-21	0.95%	1.08%	0.32%	7.08%
Nov-21	0.47%	-0.04%	1.17%	7.04%
Dec-21	-0.12%	0.84%	0.67%	7.94%

Note: a) Thailand's monthly data was extracted from the Bureau of Trade and Economic Indices – Minister of Commerce. Retrieved from: http://www.price.moc.go.th/
b) Brazilian's data was extracted from table 6070 of the System of Automatic Retriever (SIDRA) of the Brazilian Instituto of Geography and Statistics (IBGE).

Table A- 3

Core Inflation – 2018-2019

MONTHLY INFLATION (MoM)			ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
Jan-18	0.03%	0.2%	0.03%	0.20%
Feb-18	0.07%	0.47%	0.10%	0.67%

Core Inflation – 2018-2019

	MONTHLY INFLATION (MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
Mar-18	0.04%	0.14%	0.14%	0.81%
Apr-18	0.03%	0.21%	0.17%	1.02%
May-18	0.17%	0.11%	0.34%	1.13%
Jun-18	0.11%	0.24%	0.45%	1.38%
Jul-18	0.04%	0.45%	0.49%	1.83%
Aug-18	0.01%	0.14%	0.50%	1.98%
Sep-18	0.14%	0.3%	0.64%	2.28%
Oct-18	0.04%	0.21%	0.68%	2.50%
Nov-18	0%	0.05%	0.68%	2.55%
Dec-18	0.01%	0.53%	0.69%	6.66%
Jan-19	0.04%	0.39%	0.04%	0.39%
Feb-19	-0.02%	0.33%	0.01%	0.72%
Mar-19	0.02%	0.3%	0.04%	1.02%
Apr-19	0.06%	0.46%	0.10%	1.49%
May-19	0.1%	0.09%	0.20%	1.58%
Jun-19	0.05%	0.34%	0.25%	1.92%
Jul-19	-0.03%	0.25%	0.22%	2.18%
Aug-19	0.09%	0.14%	0.31%	2.32%
Sep-19	0.09%	0.09%	0.40%	2.41%
Oct-19	0.04%	0.21%	0.44%	2.63%
Nov-19	0.03%	0.29%	0.50%	2.93%
Dec-19	0 .03%	0.52%	0.50%	2.93%

*Note:*a) Thailand’s monthly data refer to “base consumer price index (Cod. 9300)” , extracted from the Bureau of Trade and Economic Indices – Minister of Commerce. Retrieved from: http://www.price.moc.go.th/
b) Brazilian’s montly data refer to Broad National Consumer Price Index - Ex-Food and Energy (EXFE) core (COD 28751), extracted for dataset of Time-series management System . Central Bank of Brazil (BACEN)

Table A- 4

Core Inflation – 2020 - 2021

	MONTHLY INFLATION (MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2020	0.02%	0.13%	0.02%	0.13%
FEB/2020	-1.92%	0.46%	-1.90%	0.59%
MAR/2020	-0.02%	-0.01%	-1.92%	0.58%
APR/2020	-0.07%	-0.01%	-1.99%	0.57%
MAY/2020	-0.3%	-0.2%	-2.28%	0.37%
JUN/2020	-0.01%	0.03%	-2.29%	0.40%
JUL/2020	0.41%	0.07%	-1.89%	0.47%
AGO/2020	0%	0.13%	-1.89%	0.60%
SEP/2020	0.04%	-0.13%	-1.85%	0.47%
OUT/2020	-0.02%	0.57%	-1.87%	1.04%
NOV/2020	0.01%	0.33%	-1.86%	1.38%
DEZ/2020	0.15%	0.7%	-1.72%	2.09%
JAN/2021	0.03%	0.26%	0.03%	0.26%
FEB/2021	-0.08%	0.53%	-0.05%	0.79%
MAR/2021	0.03%	0.21%	-0.02%	1.00%
APR/2021	0.14%	0.4%	0.12%	1.41%
MAY/2021	-0.11%	0.35%	0.01%	1.76%
JUN/2021	0.02%	0.42%	0.03%	2.19%
JUL/2021	0.03%	0.48%	0.06%	2.68%
AGO/2021	-0.07%	0.45%	-0.01%	3.14%
SEP/2021	0.16%	0.61%	0.15%	3.77%
OCT/2021	0.41%	0.99%	0.56%	4.80%

Core Inflation – 2020 - 2021

	MONTHLY INFLATION (MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
NOV/2021	0.01%	0.39%	0.57%	5.21%
DEZ/2021	0.05%	0.91%	0.62%	6.16%

Note: a) Thailand's monthly data refer to "base consumer price index (Cod. 9300)", extracted from the Bureau of Trade and Economic Indices – Minister of Commerce. Retrieved from: http://www.price.moc.go.th/
b) Brazilian's monthly data refer to Broad National Consumer Price Index - Ex-Food and Energy (EXFE) core (COD 28751), extracted for dataset of Time-series management System. Central Bank of Brazil (BACEN)

Table A- 5

Energy Inflation – 2018 -2019

	MONTHLY INFLATION(MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
Jan-18	0.03%	-3.48%	0.03%	-3.48%
Feb-18	-1.92%	0.06%	-1.89%	-3.42%
Mar-18	-0.15%	0.47%	-2.04%	-2.97%
Apr-18	0.03%	0.7%	-2.01%	-2.29%
May-18	2.85%	2.51%	0.78%	0.16%
Jun-18	-0.38%	6.82%	0.40%	6.99%
Jul-18	0.48%	3.84%	0.88%	11.10%
Aug-18	0.68%	0.49%	1.57%	11.65%
Sep-18	1.46%	0.43%	3.05%	12.13%
Oct-18	0.13%	0.12%	3.19%	12.26%
Nov-18	-2.84%	-2.84%	0.26%	9.07%
Dec-18	-4.41%	-1.23%	-4.17%	7.73%
Jan-19	-1.47%	-0.06%	-1.47%	-0.06%

Energy Inflation – 2018 -2019

	MONTHLY INFLATION(MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
Feb-19	1.67%	0.71%	0.18%	0.65%
Mar-19	2.85%	0.17%	3.03%	0.82%
Apr-19	1.55%	0.12%	4.63%	0.94%
May-19	0.01%	1.91%	4.64%	2.87%
Jun-19	-3.76%	-0.82%	0.70%	2.03%
Jul-19	1.05%	3.27%	1.76%	5.36%
Aug-19	-1.24%	2.62%	0.50%	8.12%
Sep-19	0.14%	-0.04%	0.64%	8.08%
Oct-19	-1.1%	-2.23%	-0.47%	5.67%
Nov-19	0.14%	1.8%	-0.33%	7.57%
Dec-19	0.29%	-3.13%	-0.04%	4.20%

Note: a) Thailand's monthly data refer to " energy (Cod 9200)" , extracted from the Bureau of Trade and Economic Indices – Minister of Commerce. Retrieved from: http://www.price.moc.go.th/
b) Brazilian's data was extracted from table 1419 of the System of Automatic Retriever (SIDRA) of the Brazilian Instituto of Geography and Statistics (IBGE).

Table A- 6

Energy Inflation – 2020 - 2021

	MONTHLY INFLATION(MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2020	0.07%	0.31%	0.07%	0.00%
FEB/2020	-1.92%	-1.3%	-1.85%	-1.30%
MAR/2020	-6.70%	0.2%	-8.43%	-1.10%
APR/2020	-19.22%	-0.55%	-26.03%	-1.65%

Energy Inflation – 2020 - 2021

	MONTHLY INFLATION(MoM)		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL
MAY/2020	2.73%	-0.7%	-24.01%	-2.34%
JUN/2020	16.78%	0%	-11.26%	-2.34%
JUL/2020	2.18%	2.03%	-9.32%	-0.35%
AGO/2020	0.10%	0.27%	-9.23%	-0.08%
SEP/2020	-1.02%	0.35%	-10.16%	0.27%
OUT/2020	0.37%	0.28%	-9.82%	0.55%
NOV/2020	0.50%	0.32%	-9.37%	0.87%
DEZ/2020	2.86%	7.64%	-6.78%	8.58%
JAN/2021	2.17%	-3.79%	2.17%	-3.79%
FEB/2021	-4.68%	0.13%	-2.61%	-3.66%
MAR/2021	2.23%	1.65%	-0.44%	-2.08%
APR/2021	8.71%	0.22%	11.33%	-1.86%
MAY/2021	-6.00%	4.44%	1.74%	2.50%
JUN/2021	1.95%	1.94%	3.72%	4.49%
JUL/2021	-0.30%	6.91%	3.41%	11.71%
AGO/2021	-1.20%	1.4%	0.00%	13.27%
SEP/2021	11.76%	5.79%	14.18%	19.83%
OCT/2021	2.82%	1.65%	17.40%	21.8%
NOV/2021	0.61%	1.44%	18.12%	23.55%
DEC/2021	-2.59%	0.65%	15.06%	24.36%

Note: a) Thailand's monthly data refer to "energy (Cod 9200)" , extracted from the Bureau of Trade and Economic Indices – Minister of Commerce. Retrieved from: http://www.price.moc.go.th/
b) Brazilian's data was extracted from table 6070 of the System of Automatic Retriever (SIDRA) of the Brazilian Instituto of Geography and Statistics (IBGE).

Table A- 7

Nominal Effective Exchange Rate 2018-2019

	MONTHLY		MONTHLY VARIATION		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2018	114.14	215.44	0	0.00	0.00	0.0
FEB/2018	114.75	218.58	-0.39%	1.46%	0.53%	1.5%
MAR/2018	115.45	220.7	-0.18%	0.97%	1.15%	2.4%
APR/2018	115.84	229.18	0.78%	3.84%	1.49%	6.4%
MAY/2018	115.37	236.29	0.45%	3.10%	1.08%	9.7%
JUN/2018	114.53	239.84	-0.15%	1.50%	0.34%	11.3%
JUL/2018	113.26	239.76	-0.33%	-0.03%	-0.77%	11.3%
AGO/2018	115.15	241.4	0.51%	0.68%	0.88%	12.0%
SEP/2018	117.28	247.02	0.28%	2.33%	2.75%	14.7%
OUT/2018	117.32	225.54	0.14%	-8.70%	2.79%	4.7%
NOV/2018	116.57	225.72	0.35%	0.08%	2.13%	4.8%
DEZ/2018	117.17	231.49	-0.36%	2.56%	2.65%	7.4%
JAN/2019	119.11	225.38	0.33%	-2.64%	1.66%	-2.6%
FEB/2019	121.02	223.65	0.15%	-0.77%	3.29%	-3.4%
MAR/2019	119.68	228.69	0.20%	2.25%	2.14%	-1.2%
APR/2019	119.41	230.52	0.61%	0.80%	1.91%	-0.4%
MAY/2019	120.52	233.14	1.07%	1.14%	2.86%	0.7%
JUN/2019	122.61	225.88	0.13%	-3.11%	-2.41%	-2.4%
JUL/2029	123.59	221.76	0.01%	-1.82%	5.48%	-4.2%
AGO/2019	125.18	227.75	-0.30%	2.70%	6.84%	-1.6%
SEP/2018	126.22	230.81	0.12%	1.34%	7.72%	-0.3%
OCT/2019	126.85	228.75	0.10%	-0.89%	8.26%	-1.2%

Nominal Effective Exchange Rate 2018-2019

	MONTHLY		MONTHLY VARIATION		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL	THAILAND	BRAZIL
NOV/2019	126.92	232.43	0.35%	1.61%	8.32%	0.4%
DEZ/2019	126.74	230.28	-0.13%	-0.93%	8.17%	-0.5%

Note: a)Thailand's monthly dataset was extracted from the Bank of Thailand (BoT), retrieved from: https://www.bot.or.th/App/BTWS_STAT/statistics/BOTWEBSTAT.aspx?reportID=407&language=ENG. Monthly variation is form authors calculation.
b)The NEER for Thai Baht reflects movements of the Thai baht relative to other currencies. The NEER is often used to analyze the country's price competitiveness.
Brazilian's monthly data (COD. 20360) were extracted from dataset of time-series management System. Central Bank of Brazil (BACEN) Monthly variation is form authors calculation.

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Nominal Effective Exchange Rate 2020 - 2021

	NEER MONTLY INDEX		MONTHLY VARIATION		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2020	125.14	233.15	-1.26	1.25	-1.26	1.2
FEB/2020	123.02	241.44	-1.69	3.56	-2.94	4.8
MAR/2020	121.71	268.99	-1.06	11.41	-3.97	16.8
APR/2020	120.88	289.01	-0.68	7.44	-4.62	25.5
MAY/2020	122.56	305.82	1.39	5.82	-3.30	32.8
JUN/2020	124.21	283.97	1.35	-7.14	-2.00	23.3
JUL/2020	122.55	291.09	-1.34	2.51	-3.31	26.4
AGO/2020	122.21	303.98	-0.28	4.43	-3.57	32.0
SEP/2020	121.13	301.02	-0.88	-0.97	-4.43	30.7
OUT/2020	121.23	314.31	0.08	4.41	-4.35	36.5
NOV/2020	123.03	306.20	1.48	-2.58	-9.78	33.0

Nominal Effective Exchange Rate 2020 - 2021

	NEER MONTLY INDEX		MONTHLY VARIATION		ACCUMULATED ON YEAR	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2020	125.14	233.15	-1.26	1.25	-1.26	1.2
DEZ/2020	123.17	292.76	0.11	-4.39	-2.82	27.1
JAN/2021	123.03	304.05	-0.11	3.86	-0.11	3.9
FEB/2021	123.48	305.93	0.37	0.62	0.25	4.5
MAR/2021	121.86	315.26	-1.31	3.05	-1.06	7.7
APR/2021	119.75	311.17	-1.73	-1.30	-2.78	6.3
MAY/2021	119.17	297.59	-0.48	-4.36	-3.25	1.6
JUN/2021	118.91	282.03	-0.22	-5.23	-7.16	-3.7
JUL/2021	115.80	285.82	-2.62	1.34	-5.98	-2.4
AGO/2021	114.27	289.88	-1.32	1.42	-7.23	-1.0
SEP/2021	114.35	290.82	0.07	0.32	-7.16	-0.7
OCT/21	113.69	303.5	-0.01	4.36	-0.08	3.67
NOV/21	115.54	302.83	0.02	-0.22	-0.06	3.44
DEC/21	114.41	306.61	-0.01	1.25	-0.07	4.73

Note: a)Thailand’s monthly dataset was extracted from the Bank of Thailand (BoT), retrieved from: https://www.bot.or.th/App/BTWS_STAT/statistics/BOTWEBSTAT.aspx?reportID=407&language=ENG. Monthly variation is form authors calculation.
b)The NEER for Thai Baht reflects movements of the Thai baht relative to other currencies. The NEER is often used to analyze the country’s price competitiveness. An increase in NEER refers to the baht appreciation against Thailand’s major trading partners and competitors. This reflects relative disadvantage of the baht in price competitiveness.
Brazilian’s monthly data (COD. 20360) were extracted from dataset of time-series management System. Central Bank of Brazil (BACEN) Monthly variation is form authors calculation.

Table A- 9

Trade Balance Processed Food and Agro-Based products – 2018 – 2019
(In Thousands of US Dollar)

	IMPORTS		EXPORTS		NET EXPORT	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2018	665,504.00	454,420.00	2,255,319.00	1,564,187.00	1,589,815.00	1,109,767.00

Trade Balance Processed Food and Agro-Based products – 2018 – 2019
(In Thousands of US Dollar)

FEB/2018	597,468.00	416,828.00	2,133,295.00	1,666,758.00	1,535,827.00	1,249,930.00
MAR/2018	732,708.00	453,358.00	2,394,492.00	1,851,372.00	1,661,784.00	1,398,014.00
APR/2018	730,154.00	451,061.00	2,119,847.00	1,625,646.00	1,389,693.00	1,174,585.00
MAY/2018	763,703.00	431,155.00	2,397,772.00	1,977,021.00	1,634,069.00	1,545,866.00
JUN/2018	697,075.00	382,029.00	2,393,411.00	1,823,521.00	1,696,336.00	1,441,492.00
JUL/2018	577,247.00	445,538.00	2,310,171.00	1,942,434.00	1,732,924.00	1,496,896.00
AGO/2018	778,957.00	423,738.00	2,497,063.00	1,859,736.00	1,718,106.00	1,435,998.00
SEP/2018	647,764.00	452,867.00	2,254,455.00	1,863,302.00	1,606,691.00	1,410,435.00
OUT/2018	742,133.00	503,757.00	2,433,754.00	1,671,487.00	1,691,621.00	1,167,730.00
NOV/2018	690,212.00	491,462.00	2,365,893.00	1,533,486.00	1,675,681.00	1,042,024.00
DEZ/2018	638,558.00	417,727.00	2,243,861.00	1,876,574.00	1,605,303.00	1,458,847.00
JAN/2019	841,016.00	444,664.00	2,207,877.00	1,272,146.00	1,366,861.00	827,482.00
FEB/2019	589,722.00	444,569.00	2,134,967.00	1,237,978.00	1,545,245.00	793,409.00
MAR/2019	626,757.00	421,829.00	2,329,170.00	1,427,986.00	1,702,413.00	1,006,157.00
APR/2019	765,106.00	422,040.00	2,146,694.00	1,409,068.00	1,381,588.00	987,028.00
MAY/2019	768,629.00	472,618.00	2,437,905.00	1,747,910.00	1,669,276.00	1,275,292.00
JUN/2019	766,454.00	384,092.00	2,269,560.00	1,527,596.00	1,503,106.00	1,143,504.00
JUL/2019	674,640.00	475,055.00	2,285,665.00	1,705,512.00	1,611,025.00	1,230,457.00
AGO/2019	687,933.00	414,566.00	2,285,249.00	1,571,905.00	1,597,316.00	1,157,339.00
SEP/2018	685,093.00	406,427.00	2,293,175.00	1,608,082.00	1,608,082.00	1,201,655.00
OCT/2019	664,692.00	479,324.00	2,515,812.00	1,647,794.00	1,851,120.00	1,168,470.00
NOV/2019	749,576.00	447,038.00	2,365,233.00	1,639,687.00	1,615,657.00	1,192,649.00
DEZ/2019	736,602.00	436,508.00	2,143,875.00	1,656,277.00	1,407,273.00	1,219,769.00

Note. Thailand's and Brazil's data were extracted from trademap database, of the International Trade Centre.

Table A- 10

Trade Balance Processed Food and Agro-Based Product – 2020 - 2021
(In Thousands of US Dollar)

	IMPORTS		EXPORTS		NET EXPORT	
DATE	THAILAND	BRAZIL	THAILAND	BRAZIL	THAILAND	BRAZIL
JAN/2020	734,463.00	446,442.00	1,997,928.00	1,269,674.00	1,263,465.00	823,232.00
FEB/2020	582,131.00	402,454.00	2,012,744.00	1,167,951.00	1,430,613.00	765,497.00
MAR/2020	690,774.00	492,525.00	2,317,561.00	1,551,816.00	1,626,787.00	1,059,291.00
APR/2020	707,648.00	374,537.00	2,325,008.00	1,564,604.00	1,617,360.00	1,190,067.00
MAY/2020	664,624.00	321,258.00	2,212,932.00	2,017,789.00	1,548,308.00	1,696,531.00
JUN/2020	704,543.00	355,858.00	2,100,705.00	2,016,262.00	1,396,162.00	1,660,404.00
JUL/2020	666,461.00	454,303.00	2,043,206.00	2,098,873.00	1,376,745.00	1,644,570.00
AGO/2020	636,005.00	390,145.00	2,100,036.00	1,971,968.00	1,464,031.00	1,581,823.00
SEP/2020	702,784.00	487,037.00	2,135,521.00	2,085,040.00	1,432,737.00	1,598,003.00
OUT/2020	647,002.00	600,057.00	2,158,748.00	2,259,954.00	1,511,746.00	1,659,897.00
NOV/2020	717,327.00	666,585.00	2,240,309.00	2,023,115.00	1,522,982.00	1,356,530.00
DEZ/2020	731,414.00	607,161.00	2,005,566.00	1,912,641.00	1,274,152.00	1,305,480.00
JAN/2021	658,499.00	570,272.00	1,900,211.00	1,572,053.00	1,241,712.00	1,001,781.00
FEB/2021	698,394.00	546,004.00	1,957,917.00	1,639,159.00	1,259,523.00	1,093,155.00
MAR/2021	761,230.00	551,644.00	2,218,787.00	1,907,023.00	1,457,557.00	1,355,379.00
APR/2021	745,812.00	485,314.00	2,095,395.00	2,112,951.00	1,349,583.00	1,627,637.00
MAY/2021	874,094.00	488,979.00	2,184,950.00	2,391,635.00	1,310,856.00	1,902,656.00
JUN/2021	837,478.00	513,118.00	2,340,844.00	2,532,176.00	1,503,366.00	2,019,058.00
JUL/2021	746,900.00	490,917.00	2,041,009.00	2,486,189.00	1,294,109.00	1,995,272.00
AGO/2021	828,858.00	534,881.00	2,123,555.00	2,433,554.00	1,294,697.00	1,898,673.00
SEP/2021	881,363.00	490,612.00	2,401,740.00	2,315,486.00	1,520,377.00	1,824,874.00
OCT/2021	677,909.00	581,492.00	2,442,695.00	2,275,951.00	1,764,786.00	1,694,459.00
NOV/2021	755,284.00	568,628.00	2,498,678.00	2,306,398.00	1,743,394.00	1,737,770.00
DEZ/2021	740,093.00	576,175.00	2,418,486.00	2,385,965.00	1,678,393.00	1,809,790.00

Note: Both Thailand and Brazilian data were extracted from trade map database, of the International Trade Centre.

Table A- 11

Crude Oil Global Price – 2018 - 2019

DATE	index	Change over the Previous Period	PRICE in US$
JAN/2018	149.22	8.07%	US$ 66.15
FEB/2018	141.81	-4.11%	US$ 63.44
MAR/2018	143.34	1.19%	US$ 64.20
APR/2018	153.86	7.17%	US$ 68.79
MAY/2018	167.08	6.62%	US$ 73.34
JUN/2018	165.24	-1.81%	US$ 71.99
JUL/2018	167.92	0.99%	US$ 72.72
AGO/2018	165.28	-2.26%	US$ 71.06
SEP/2018	174.66	6.05%	US$ 75.36
OUT/2018	179.06	1.83%	US$ 76.73
NOV/2018	146.29	-18.67%	US$ 62.38
DEZ/2018	126.08	-13.77%	US$ 53.79
JAN/2019	131.42	4.90%	US$ 56.43
FEB/2019	142.53	8.29%	US$ 61.10
MAR/2019	148.86	4.40%	US$ 63.79
APR/2019	160.45	7.47%	US$ 68.57
MAY/2019	157.12	-2.47%	US$ 66.88
JUN/2019	139.92	-10.71%	US$ 59.73
JUL/2019	144.45	2.93%	US$ 61.47
AGO/2019	136.17	-6.31%	US$ 57.60
SEP/2018	142.33	4.18%	US$ 60.01
OCT/2019	135.55	-4.51%	US$ 57.30
NOV/2019	142.60	5.44%	US$ 60.42
DEZ/2019	149.22	4.93%	US$ 63.40

Crude Oil Global Price – 2018 - 2019

DATE	index	Change over the Previous Period	PRICE in US$

Note: Crude Oil (petroleum) is composed of a simple average of three spot prices: Dated Brent, West Texas Intermediate, and the Dubai Fateh.
Data extracted from the International Monetary Fund (IMF). FMI eLIBC_BRary data. Primary Commodity price System. Retrieved from: https://data.imf.org/?sk=471DDDF8-D8A7-499A-81BA-5B332C01F8B9&sId=1547558078595

Table A- 12

Crude Oil Global Price – 2020 -2021

DATE	index	Change over the Previous Period	PRICE in US$
JAN/2020	145.14	-2.67%	UD$ 61.68
FEB/2020	126.53	-13.49%	UD$ 53.37
MAR/2020	76.22	-39.64%	UD$ 32.20
APR/2020	50.45	-34.22%	UD$ 21.17
MAY/2020	72.25	43.24%	UD$ 30.35
JUN/2020	92.83	29.98%	UD$ 39.46
JUL/2020	98.08	6.61%	UD$ 42.07
AGO/2020	99.85	3.25%	UD$ 43.44
SEP/2020	93.32	-6.53%	UD$ 40.60
OUT/2020	91.57	-1.75%	UD$ 39.90
NOV/2020	96.88	6.37%	UD$ 42.44
DEZ/2020	110.07	14.89%	UD$ 48.75
JAN/2021	120.32	9.70%	UD$ 53.49
FEB/2021	136.26	13.03%	UD$ 60.47
MAR/2021	145.10	5.56%	UD$ 63.83
APR/2021	142.87	-1.43%	UD$ 62.93
MAY/2021	149.65	5.57%	UD$ 66.43
JUN/2021	162.28	8.08%	UD$ 71.80
JUL/2021	167.08	2.08%	UD$ 73.28

Crude Oil Global Price – 2020 -2021

DATE	index	Change over the Previous Period	PRICE in US$
AGO/2021	157.23	-5.99%	UD$ 68.89
SEP/2021	166.18	5.61%	UD$ 72.77
OCT/2021	188.48	12.78%	UD$ 82.06
NOV/2021	184.64	-2.63%	UD$ 79.89
DEZ/2021	169.41	-8.66%	UD$ 72.98

Note: Crude Oil (petroleum) is composed of a simple average of three spot prices: Dated Brent, West Texas Intermediate, and the Dubai Fateh.
Data extracted from the International Monetary Fund (IMF). FMI eLIBC_BRary data. Primary Commodity price System. Retrieved from: https://data.imf.org/?sk=471DDDF8-D8A7-499A-81BA-5B332C01F8B9&sId=1547558078595

Table A- 13

Commodity Price: Food and Beverage

Month	Index				Change over the Previous Period			
	2018	2019	2020	2021	2018	2019	2020	2021
January	104.43	99.12	104.14	114.34	3.32%	1.76%	1.07%	5.94%
February	104.66	97.62	100.12	117.39	0.21%	-1.51%	-3.86%	2.67%
March	105.77	96.78	96.44	120.01	1.06%	-0.86%	-3.67%	2.23%
April	105.64	100.00	92.42	126.84	-0.13%	3.32%	-4.17%	5.69%
May	107.16	96.78	95.63	134.27	1.44%	-3.22%	3.48%	5.86%
June	102.91	98.98	98.42	129.29	-3.97%	2.28%	2.92%	-3.71%
July	100.19	99.06	96.49	130.15	-2.65%	0.08%	-1.96%	0.66%
August	96.18	96.93	97.94	130.76	-3.99%	-2.15%	1.50%	0.47%
September	97.25	95.08	99.35	128.34	1.11%	-1.91%	1.44%	-1.85%
October	99.31	95.42	103.79	130.51	2.11%	0.36%	4.47%	1.69%
November	95.10	99.41	106.79	131.91	-4.24%	4.19%	2.89%	1.07%
December	97.40	103.04	107.93	134.73	2.42%	3.65%	1.06%	2.14%

Note: Data extracted from the International Monetary Fund (IMF). FMI eLIBC_BRary data. Primary Commodity price System. Retrieved from: https://data.imf.org/?sk=471DDDF8-D8A7-499A-81BA-5B332C01F8B9&sId=15475580785

Table A- 14

Thailand Degree of Openness. Quarterly data

Date	Import (TBH)	EXPORT(TBH)	GDP	Degree of Openness
2018/Q1	102,588.94	236,948.27	4,053,070	8.377284626
2018/Q2	101,256.98	255,445.11	3,999,458	8.918760742
2018/Q3	96,790.31	264,353.63	4,065,277	8.883624412
2018/Q4	106,148.51	255,199.45	4,255,538	8.491240356
2019/Q1	103,490.19	236,188.39	4,220,390	8.04851163
2019/Q2	105,314.42	250,802.53	4,154,137	8.572585594
2019/Q3	95,375.67	244,711.18	4,179,947	8.136152205
2019/Q4	101,431.59	232,551.08	4,337,937	7.699112965
2020/Q1	107,340.65	225,500.57	4,137,075	8.045327194
2020/Q2	101,019.53	274,767.52	3,534,836	10.63096138
2020/Q3	101,428.08	234,270.60	3,853,530	8.711458844
2020/Q4	108,028.57	220,695.46	4,111,450	7.995330844
2021/Q1	111,899.43	218,655.45	4,053,192	8.155421209
2021/Q2	121,396.78	284,443.66	3,913,505	10.3702548
2021/Q3	117,389.24	270,464.35	3,917,629	9.900212348
2021/Q4	116,275.28	275,741.90	4,295,500	9.12622931

Note. The Units are in billions of baht. For Thailand, the quarterly data in THB was used because this data was not found in USD or in higher frequency. 2) The data relating to trade was extracted from the Bank of Thailand from the table: EC_XT_001: Trade Classified by Commodity Group. Retrieved date : 14 Sep 2022 23:48.

Table A- 15

Brazil degree of Openness and monthly DGP

Degree of Openness				
	2018	2019	2020	2021
January	3.42649136	3.984921066	5.307767383	4.774973851
February	3.602472725	4.561258092	4.016679316	5.265516631
Mach	4.930627381	5.133114817	4.862060183	8.684458924
April	5.114011093	5.116272379	8.795882426	9.82601852
May	6.464693134	5.234228697	9.96676101	9.882722283
June	5.7351279	5.837239427	9.209808636	8.792609544
July	6.502587233	4.834437292	8.281359187	8.239322147
August	6.355535035	5.851387293	8.919943743	8.390293244
September	6.012349674	5.618112451	7.532596514	8.096181434
October	5.15582234	5.242585523	7.388643533	7.607448018
November	5.215285816	5.777505738	6.658239205	7.188720233
December	5.405983876	5.345161101	5.977140613	7.776719306
Monthly DGP (Thousands of USD)				
	2018	2019	2020	2021
January	171,471,000.00	154,560,000.00	121,421,000.00	145,802,000.00
February	165,809,000.00	154,933,000.00	124,344,000.00	139,664,000.00

Mach	178,791,000.00	156,815,000.00	129,991,000.00	127,212,000.00
April	171,457,000.00	157,795,000.00	128,078,000.00	103,969,000.00
May	153,650,000.00	154,239,000.00	134,468,000.00	996,360,000.00
June	153,909,000.00	155,091,000.00	142,021,000.00	113,553,000.00
July	153,755,000.00	167,458,000.00	144,102,000.00	118,203,000.00
August	151,607,000.00	156,636,000.00	141,077,000.00	113,053,000.00
September	139,364,000.00	150,057,000.00	138,717,000.00	116,356,000.00
October	162,220,000.00	158,730,000.00	133,700,000.00	116,339,000.00
November	159,998,000.00	152,919,000.00	135,845,000.00	121,820,000.00
December	154,181,000.00	153,568,000.00	135,069,000.00	132,392,000.00

Table A- 16

DGP Proxy.

Brazil IBC_BR	2018	2019	2020	2021
January	137.31	139.04	139.65	140.04
February	137.32	138.34	140.57	142.56
Mach	137.1	137.89	131.18	137.35
April	137.97	137.63	118.31	138.57
May	133.14	138.68	121.19	138.9
June	137.21	138.56	127.04	138.71
July	137.75	138.15	131.22	138.88
August	138.79	138.04	133.92	138.94
September	137.97	139.04	136.51	138.74
October	138.07	140.01	138.63	139.08
November	138.19	139.32	138.61	140.32
December	139.04	139.04	139.31	141.16
Thailand LEI	**2018**	**2019**	**2020**	**2021**
January	149.95	151.65	151.44	157.49
February	150.93	151.28	151.84	157.6
Mach	152.09	151.06	153.96	160.44
April	150.8	150.19	153.41	157.56
May	150.35	151.17	153.39	158.38
June	150.21	151.49	154.94	158.11
July	150.41	151.48	155.61	157.06

August	149.57	152.09	156.56	157.38
September	150.85	152.44	156.73	158.53
October	149.53	153.86	157.22	158.2
November	153.44	152.16	157.7	158.9
December	151.92	151.43	158.56	160.66

Note: IBC_BR (Central Bank Economic Activity Index). Retrieved from: https://www3.bcb.gov.br/sgspub/consultarmetadados/consultarMetadadosSeries.do?method=consultarMetadadosSeriesInternet&hdOidSerieSelecionada=24363
LEI(Leading Economic Index). Calculated by the Bank of Thailand

Table A- 17

Monetary Policy (end of Period)

Date	Thailand's Exchange Rate	Thailand's Interest Rates	Brazil's Exchange	Brazil's Interest Rate
Jan-18	31.3762	1.50	3.1618	7.1
Feb-18	31.4627	1.50	3.2443	6.75
Mar-18	31.2318	1.50	3.3232	6.5
Apr-18	31.4986	1.50	3.4805	6.5
May-18	32.0247	1.50	3.7364	6.5
Jun-18	33.1672	1.50	3.8552	6.5
Jul-18	33.3093	1.50	3.7543	6.5
Aug-18	32.742	1.50	4.1347	6.5
Sep-18	32.4066	1.75	4.0033	6.5
Oct-18	33.2714	1.75	3.7171	6.5
Nov-18	32.9178	1.75	3.8627	6.5
Dec-18	32.4498	1.75	3.8742	6.5
Jan-19	31.2458	1.75	3.6513	6.5
Feb-19	31.4767	1.50	3.7379	6.5
Mar-19	31.8117	1.50	3.8961	6.5
Apr-19	31.9338	1.25	3.9447	6.5
May-19	31.7553	1.25	3.9401	6.5
Jun-19	30.7443	1.00	3.8316	6
Jul-19	30.7965	0.75	3.7643	6
Aug-19	30.6443	0.75	4.1379	6
Sep-19	30.5919	0.50	4.1638	6
Oct-19	30.1829	0.50	4.0035	5.5

Monetary Policy (end of Period)

Date	Thailand's Exchange Rate	Thailand's Interest Rates	Brazil's Exchange	Brazil's Interest Rate
Nov-19	30.2264	0.50	4.2234	5
Dec-19	30.154	0.50	4.0301	4.5
Jan-20	31.1307	0.50	4.2689	4.5
Feb-20	31.6225	0.50	4.4981	4.25
Mar-20	32.6712	0.50	5.1981	4.25
Apr-20	32.3781	0.50	5.4264	3.75
May-20	31.845	0.50	5.4257	3
Jun-20	30.8905	0.50	5.4754	2.25
Jul-20	31.2596	0.50	5.2027	2.25
Aug-20	31.0874	0.50	5.4707	2
Sep-20	31.6579	0.50	5.6401	2
Oct-20	31.1977	0.50	5.7712	2
Nov-20	30.2805	1.50	5.3311	2
Dec-20	30.0371	1.50	5.1961	2
Jan-21	29.9928	1.50	5.4753	2
Feb-21	30.0434	1.50	5.5296	2
Mar-21	31.3394	1.50	5.6967	2.75
Apr-21	31.195	1.50	5.403	2.75
May-21	31.2629	1.50	5.2316	3.5
Jun-21	32.0533	1.50	5.0016	4.25
Jul-21	32.9018	1.75	5.121	4.25
Aug-21	32.3856	1.75	5.1427	5.25
Sep-21	33.9223	1.75	5.4388	6.25
Oct-21	33.1805	1.75	5.6424	7.75

Monetary Policy (end of Period)

Date	Thailand's Exchange Rate	Thailand's Interest Rates	Brazil's Exchange	Brazil's Interest Rate
Nov-21	33.6898	1.75	5.6193	7.75
Dec-21	33.4199	1.50		9.25

Note. Thailand's exchange rate (domestic currency per us dollar). Source: International Financial Statistics of the International Monetary Fund.
Thailand's Interest Rate, retrieved from the Bank of Thailand.
Brazil's exchange rate (domestic currency per us dollar). Source: International Financial Statistics of the International Monetary Fund.
Brazil's Interest Rate retrieved from the Central Bank of Brazil.

Table A- 18

Agrarian Production

Date	Brazilian Agricultural Production (LSPA)	Brazilian Agricultural Price Index (IPPAs/CEPEA)	Thailand's Agricultural Production Index	Thailand's Production Index
Jan-18	1,185,753,186.00	93.1	149.58	124.43
Feb-18	1,189,268,614.00	94.3	144.59	126.11
Mar-18	1,196,376,025.00	99	149.33	131.4
Apr-18	1,224,610,063.00	98.7	122.56	128.36
May-18	1,219,893,960.00	97.4	109.79	130.76
Jun-18	1,207,997,037.00	96.7	102.08	129.4
Jul-18	1,203,910,257.00	96.1	104.22	127.05
Aug-18	1,198,037,465.00	97.5	134.65	123.83
Sep-18	1,185,079,393.00	97.4	128.76	124.27
Oct-18	1,187,313,763.00	94.4	130.7	124.57
Nov-18	1,190,245,012.00	92.9	296.69	122.02
Dec-18	1,186,096,740.00	92.5	170.78	122.85
Jan-19	1,185,896,401.00	91.1	154.55	123.88
Feb-19	1,181,242,882.00	93.2	146.14	126.31
Mar-19	1,196,474,589.00	94.7	147.6	128.57
Apr-19	1,210,900,149.00	93.9	118.42	127.99
May-19	1,215,071,760.00	90.6	107.99	132.01
Jun-19	1,196,545,554.00	92.3	101.12	136.68
Jul-19	1,203,900,744.00	90.2	108.61	130.55
Aug-19	1,204,103,591.00	92.9	131.8	127.07

Agrarian Production

Date	Brazilian Agricultural Production (LSPA)	Brazilian Agricultural Price Index (IPPAs/CEPEA)	Thailand's Agricultural Production Index	Thailand's Production Index
Sep-19	1,208,351,909.00	94	130.74	127.03
Oct-19	1,209,461,110.00	95.9	136.64	125.72
Nov-19	1,209,382,380.00	101.8	286.65	127.55
Dec-19	1,210,387,193.00	104.4	166.43	129.63
Jan-20	1,224,463,734.00	102	153.71	134.97
Feb-20	1,233,186,479.00	103.5	131.27	137
Mar-20	1,223,654,995.00	108.1	111.48	139.43
Apr-20	1,224,964,358.00	108.9	102.14	132.33
May-20	1,225,312,097.00	107.9	107.56	127.92
Jun-20	1,240,403,499.00	105.3	100.71	130.36
Jul-20	1,244,694,367.00	107.7	108.1	132.93
Aug-20	1,255,691,985.00	112.4	119.66	136.66
Sep-20	1,253,478,985.00	118.5	123.27	138.93
Oct-20	1,253,994,988.00	127	138.95	141.14
Nov-20	1,253,566,744.00	130.6	328.24	139.82
Dec-20	1,244,162,903.00	119.5	164.1	144.23
Jan-21	1,248,432,911.00	121.7	150.22	143.87
Feb-21	1,250,813,812.00	118.4	134.81	148.57
Mar-21	1,255,455,541.00	118	112.9	156.13
Apr-21	1,239,584,304.00	120.4	103.61	149.01
May-21	1,238,222,167.00	116.2	106.74	146.42
Jun-21	1,228,519,882.00	112.3	103.55	144.33
Jul-21	1,224,494,683.00	114.1	111.07	133.92
Aug-21	1,212,730,333.00	119.7	135.79	127.85
Sep-21	1,185,446,303.00	120.8	128.77	128.22
Oct-21	1,183,739,041.00	116.4	133.07	129.85
Nov-21	1,181,969,125.00	116.4	317.4	135.52
Dec-21	1,173,302,886.00	118.3	158.88	141.12

Note. The Brazilian Agricultural Production (LSPA- Systematic Reporting of Agricultural Production) is measured by tons and it can be found at table 6588, calculated by the Brazilian Institute of Geography and Statistics (IBGE) The Brazilian Production Price Index (IPPAs) is an index calculated by the Center of Advanced Studies in Applied Economics (CEPEA). retrieved from: https://www.cepea.esalq.usp.br/br/metodologia-ippa-1.aspx

Thailand's Producer Index and Price Index can be found at table 01 and 02 respectively. Source: Office of Agricultural Economics, Ministry of Agriculture and Cooperatives. Retrieved from: Price and output indices (oae.go.th)

APPENDIX B

Statistical Outcomes

Table B - 1

Brazilian Data Unit Root Test Results
Null Hypothesis: the variable has a unit root.

At First Difference		d(BAPI)	d(BAPROD)	d(BC)	d(BENINF)	d(BER)	d(BF_BIMP)
With Constant	t-Statistic	-5.7407	-5.4336	-14.9090	-7.2815	-6.1678	-6.7993
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***	***
With Constant & Trend	t-Statistic	-5.6757	-1.0939	-14.9056	-7.1981	-6.1231	-6.7917
	Prob.	***0.0001***	***0.9165***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	n0	***	***	***	***
Without Constant & Trend	t-Statistic	-5.6879	-5.4899	-15.0441	-7.3687	-5.9367	-6.6545
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***	***

At level		BF_BINF	BF_EXP	BIR	BNEER	COI	COP
With Constant	t-Statistic	-4.5206	-3.8621	-3.8431	-0.9312	-1.4097	-1.4284
	Prob.	***0.0007***	***0.0047***	***0.0053***	***0.7695***	***0.5693***	***0.5601***
		***	***	***	n0	n0	n0
With Constant & Trend	t-Statistic	-4.7576	-4.0797	-3.0736	-1.7860	-1.1990	-1.2342
	Prob.	***0.0019***	***0.0127***	***0.1263***	***0.6956***	***0.8987***	***0.8910***
		***	**	n0	n0	n0	n0
Without Constant & Trend	t-Statistic	-3.3452	1.1485	0.4646	1.2465	-0.0994	-0.0472
	Prob.	***0.0013***	***0.9324***	***0.8109***	***0.9438***	***0.6440***	***0.6617***
		***	n0	n0	n0	n0	n0

At First Difference		d(BF_BINF)	d(BF_EXP)	d(BIR)	d(BNEER)	d(COI)	d(COP)
With Constant	t-Statistic	-5.3622	-4.2615	0.2312	-5.8952	-5.6456	-5.6372
	Prob.	***0.0001***	***0.0018***	***0.9716***	***0.0000***	***0.0000***	***0.0000***
		***	***	n0	***	***	***
	t-Statistic	-5.3790	-5.6129	0.6601	-5.8274	-5.6888	-5.6562

Brazilian Data Unit Root Test Results
Null Hypothesis: the variable has a unit root.

With Constant & Trend	Prob.	0.0004 ***	0.0003 ***	0.9994 n0	0.0001 ***	0.0001 ***	0.0001 ***
Without Constant & Trend	t-Statistic	-5.4158	-4.6203	-1.3211	-5.7594	-5.7114	-5.6990
	Prob.	0.0000 ***	0.0000 ***	0.1698 n0	0.0000 ***	0.0000 ***	0.0000 ***

At level		GFI	IBC_BR	LNBAPI	LNBAPROD	LNBC	LNBER
With Constant	t-Statistic	0.7051	-3.2460	-0.9126	-2.6380	-5.2284	-1.5624
	Prob.	0.9911 n0	0.0236 **	0.7756 n0	0.0944 *	0.0001 ***	0.4936 n0
With Constant & Trend	t-Statistic	-1.0597	-3.2130	-2.2534	-0.1884	-6.0579	-2.1659
	Prob.	0.9250 n0	0.0946 *	0.4499 n0	0.9915 n0	0.0001 ***	0.4968 n0
Without Constant & Trend	t-Statistic	1.5187	0.1102	1.1336	-0.1925	-0.8229	1.5651
	Prob.	0.9665 n0	0.7126 n0	0.9313 n0	0.6116 n0	0.3523 n0	0.9695 n0

At First Difference		d(GFI)	d(IBC_BR)	d(LNBAPI)	d(LNBAPROD)	d(LNBC)	d(LNBER)
With Constant	t-Statistic	-5.4011	-5.1225	-5.6688	-5.4180	-5.3912	-6.3759
	Prob.	0.0000 ***	0.0001 ***	0.0000 ***	0.0000 ***	0.0001 ***	0.0000 ***
With Constant & Trend	t-Statistic	-5.8962	-5.0760	-5.6044	-1.0912	-5.3506	-6.3678
	Prob.	0.0001 ***	0.0008 ***	0.0002 ***	0.9170 n0	0.0006 ***	0.0000 ***
Without Constant & Trend	t-Statistic	-5.2557	-5.1784	-5.6043	-5.4739	-5.4306	-6.0897
	Prob.	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***	0.0000 ***

At level		LNBF_BEXP	LNBF_BIMP	LNBIR	LNBNEER	LNCOP	LNGFI	LNIBC_BR
With Constant	t-Statistic	-4.1774	-1.1910	-1.9291	-0.9795	-1.5773	0.4999	-3.3062
	Prob.	0.0019 ***	0.6708 n0	0.3159 n0	0.7531 n0	0.4857 n0	0.9850 n0	0.0203 **
With Constant & Trend	t-Statistic	-4.3113	-1.8361	-4.1503	-2.0494	-1.4147	-1.1852	-3.2699
	Prob.	0.0069 ***	0.6711 n0	0.0117 **	0.5594 n0	0.8431 n0	0.9020 n0	0.0841 *
Without Constant & Trend	t-Statistic	0.8592	0.9120	0.0153	1.4291	0.0962	1.3204	0.1542
	Prob.	0.8915 n0	0.9008 n0	0.6824 n0	0.9600 n0	0.7082 n0	0.9509 n0	0.7260 n0

At First Difference		d(LNBF_BEXP)	d(LNBF_BIMP)	d(LNBIR)	d(LNBNEER)	d(LNCOP)	d(LNGFI)	d(LNIBC_BR)
With Constant	t-Statistic	-4.8285	-7.8536	-2.0337	-5.7791	-5.9931	-5.4387	-5.2117
	Prob.	0.0004 ***	0.0000 ***	0.2719 n0	0.0000 ***	0.0000 ***	0.0000 ***	0.0001 ***
With	t-Statistic							

Brazilian Data Unit Root Test Results
Null Hypothesis: the variable has a unit root.

Constant	Prob.	-5.7127	-7.7988	-2.3836	-5.7126	-5.9960	-5.8676	-5.1636
With Constant & Trend	t-Statistic Prob	***0.0002*** ***	***0.0000*** ***	***0.3828*** n0	***0.0001*** ***	***0.0001*** ***	***0.0001*** ***	***0.0006*** ***
Without		-4.6787	-7.7134	-2.0410	-5.6348	-6.0607	-5.3288	-5.2692
Constant & Trend		***0.0000*** ***	***0.0000*** ***	***0.0407*** **	***0.0000*** ***	***0.0000*** ***	***0.0000*** ***	***0.0000*** ***

Note.
a: (*)Significant at the 10%; (**)Significant at the 5%; (***) Significant at the 1% and (no) Not Significant
b: Lag Length based on AIC
c: Probability based on MacKinnon (1996) one-sided p-values.

Table B - 2

Brazilian Data. Pairwise Granger Causality Test.
Lags:4

Null Hypothesis:	Obs	F-Statistic	Prob.
BIR does not Granger Cause BF_BINF	44	1.11918	0.3632
BF_BINF does not Granger Cause BIR		0.06096	0.9928
BENINF does not Granger Cause BF_BINF	44	0.78731	0.5413
BF_BINF does not Granger Cause BENINF		0.83580	0.5117
IBC_BR does not Granger Cause BF_BINF	44	2.19581	0.0896
BF_BINF does not Granger Cause IBC_BR		2.93963	0.0340
LNBIR does not Granger Cause BF_BINF	44	0.99717	0.4221
BF_BINF does not Granger Cause LNBIR		0.25407	0.9052
DIFBENINF does not Granger Cause BF_BINF	43	0.79263	0.5382
BF_BINF does not Granger Cause DIFBENINF		0.86146	0.4969
DIFBER does not Granger Cause BF_BINF	43	1.18559	0.3347
BF_BINF does not Granger Cause DIFBER		0.20401	0.9344
DIFBNEER does not Granger Cause BF_BINF	43	0.45722	0.7665
BF_BINF does not Granger Cause DIFBNEER		0.65404	0.6281
DIFCOI does not Granger Cause BF_BINF	43	0.44851	0.7727
BF_BINF does not Granger Cause DIFCOI		0.70598	0.5934
DIFCOP does not Granger Cause BF_BINF	43	0.58274	0.6772
BF_BINF does not Granger Cause DIFCOP		0.61704	0.6534
DIFGFI does not Granger Cause BF_BINF	43	1.70459	0.1717
BF_BINF does not Granger Cause DIFGFI		2.48061	0.0623

DIFIBC_BR does not Granger Cause BF_BINF	43	3.88782	0.0105
BF_BINF does not Granger Cause DIFIBC_BR		0.37566	0.8244
DIFLNBAPI does not Granger Cause BF_BINF	43	1.60019	0.1968
BF_BINF does not Granger Cause DIFLNBAPI		1.16132	0.3450
DIFLNBAPROD does not Granger Cause BF_BINF	43	1.04802	0.3971
BF_BINF does not Granger Cause DIFLNBAPROD		2.72498	0.0454
DIFLNBFEXP does not Granger Cause BF_BINF	43	0.20955	0.9313
BF_BINF does not Granger Cause DIFLNBFEXP		1.16639	0.3429
DIFLNBFIMP does not Granger Cause BF_BINF	43	1.26835	0.3015
BF_BINF does not Granger Cause DIFLNBFIMP		0.17391	0.9503
DIFLNBER does not Granger Cause BF_BINF	43	0.61368	0.6557
BF_BINF does not Granger Cause DIFLNBER		0.58760	0.6738
DIFLNBNEER does not Granger Cause BF_BINF	43	0.39709	0.8093
BF_BINF does not Granger Cause DIFLNBNEER		0.95034	0.4471
DIFLNCOI does not Granger Cause BF_BINF	43	0.36381	0.8326
BF_BINF does not Granger Cause DIFLNCOI		0.96509	0.4392
DIFLNCOP does not Granger Cause BF_BINF	43	0.69689	0.5994
BF_BINF does not Granger Cause DIFLNCOP		0.56005	0.6932
DIFLNGFI does not Granger Cause BF_BINF	43	1.62353	0.1909
BF_BINF does not Granger Cause DIFLNGFI		2.50098	0.0607
DIFLNIBC_BR does not Granger Cause BF_BINF	43	1.60995	0.1943
BF_BINF does not Granger Cause DIFLNIBC_BR		1.18217	0.3361
DIFBAPROD does not Granger Cause BF_BINF	43	0.18542	0.9444
BF_BINF does not Granger Cause DIFBAPROD		0.84342	0.5075
DIFBAPI does not Granger Cause BF_BINF	43	1.14425	0.3525
BF_BINF does not Granger Cause DIFBAPI		2.88195	0.0371
DIFBF_BIMP does not Granger Cause BF_BINF	44	1.95528	0.1230
BF_BINF does not Granger Cause DIFBF_BIMP		0.64855	0.6317
DIFBF_BEXP does not Granger Cause BF_BINF	44	2.14172	0.0963
BF_BINF does not Granger Cause DIFBF_BEXP		0.47106	0.7566

Note. All statistical tests were done by Eviews v.12.
All these variables had rejected the null hypothesis regards to unit root.

Table B - 3

Brazilian Data. Pairwise Granger Causality Test. Lags: 8

Null Hypothesis:	Obs	F-Statistic	Prob.
BIR does not Granger Cause BF_BINF	40	3.70516	0.0064
BF_BINF does not Granger Cause BIR		0.37955	0.9206
BENINF does not Granger Cause BF_BINF	40	0.67763	0.7063
BF_BINF does not Granger Cause BENINF		1.85568	0.1175
IBC_BR does not Granger Cause BF_BINF	40	1.09413	0.4021
BF_BINF does not Granger Cause IBC_BR		2.37521	0.0500
LNBIR does not Granger Cause BF_BINF	40	2.90736	0.0214
BF_BINF does not Granger Cause LNBIR		0.24351	0.9776
DIFBENINF does not Granger Cause BF_BINF	39	0.67563	0.7077
BF_BINF does not Granger Cause DIFBENINF		1.94810	0.1031
DIFBER does not Granger Cause BF_BINF	39	2.79218	0.0269
BF_BINF does not Granger Cause DIFBER		1.40431	0.2493
DIFBNEER does not Granger Cause BF_BINF	39	0.99659	0.4657
BF_BINF does not Granger Cause DIFBNEER		1.46438	0.2264
DIFCOI does not Granger Cause BF_BINF	39	0.99644	0.4658
BF_BINF does not Granger Cause DIFCOI		1.37311	0.2620
DIFCOP does not Granger Cause BF_BINF	39	1.34332	0.2747
BF_BINF does not Granger Cause DIFCOP		0.58586	0.7788
DIFGFI does not Granger Cause BF_BINF	39	0.84075	0.5776
BF_BINF does not Granger Cause DIFGFI		2.59807	0.0364
DIFIBC_BR does not Granger Cause BF_BINF	39	1.39782	0.2519
BF_BINF does not Granger Cause DIFIBC_BR		0.75491	0.6444
DIFLNBAPI does not Granger Cause BF_BINF	39	2.75965	0.0283
BF_BINF does not Granger Cause DIFLNBAPI		0.79099	0.6160
DIFLNBAPROD does not Granger Cause BF_BINF	39	0.64068	0.7356
BF_BINF does not Granger Cause DIFLNBAPROD		2.12674	0.0771

DIFLNBFEXP does not Granger Cause BF_BINF	39	0.13108	0.9970
BF_BINF does not Granger Cause DIFLNBFEXP		1.92801	0.1065
DIFLNBFIMP does not Granger Cause BF_BINF	39	2.99275	0.0198
BF_BINF does not Granger Cause DIFLNBFIMP		1.34916	0.2721
DIFLNBER does not Granger Cause BF_BINF	39	1.74533	0.1435
BF_BINF does not Granger Cause DIFLNBER		1.00096	0.4628
DIFLNBNEER does not Granger Cause BF_BINF	39	0.52094	0.8279
BF_BINF does not Granger Cause DIFLNBNEER		2.05200	0.0871
DIFLNCOI does not Granger Cause BF_BINF	39	0.51301	0.8337
BF_BINF does not Granger Cause DIFLNCOI		1.95666	0.1017
DIFLNCOP does not Granger Cause BF_BINF	39	1.44405	0.2339
BF_BINF does not Granger Cause DIFLNCOP		0.56573	0.7943
DIFLNGFI does not Granger Cause BF_BINF	39	0.85645	0.5657
BF_BINF does not Granger Cause DIFLNGFI		2.70944	0.0306
DIFLNIBC_BR does not Granger Cause BF_BINF	39	2.71465	0.0303
BF_BINF does not Granger Cause DIFLNIBC_BR		0.80396	0.6059
DIFBAPROD does not Granger Cause BF_BINF	39	0.09609	0.9990
BF_BINF does not Granger Cause DIFBAPROD		1.41638	0.2445
DIFBAPI does not Granger Cause BF_BINF	39	0.64285	0.7339
BF_BINF does not Granger Cause DIFBAPI		1.82252	0.1265
DIFBF_BIMP does not Granger Cause BF_BINF	40	1.86752	0.1152
BF_BINF does not Granger Cause DIFBF_BIMP		1.74517	0.1411
DIFBF_BEXP does not Granger Cause BF_BINF	40	1.27970	0.3016
BF_BINF does not Granger Cause DIFBF_BEXP		1.67228	0.1592

Note. All statistical tests were done by Eviews v.12.
All these variables had rejected the null hypothesis regards to unit root.

Table B - 4

BRAZILIAN DATA CORRELOGRAM A

	BF_BINF	BIR	BENINF	IBC_BR	LNBIR
BF_BINF	1.000000	-0.327577	0.002506	-0.076788	-0.347415
BIR	-0.327577	1.000000	0.044070	0.284735	0.983466
BENINF	0.002506	0.044070	1.000000	0.089762	0.046488
IBC_BR	-0.076788	0.284735	0.089762	1.000000	0.246710
LNBIR	-0.347415	0.983466	0.046488	0.246710	1.000000
DIFBENINF	-0.058231	-0.045754	0.653499	-0.034862	-0.031727
DIFBER	-0.070016	0.066639	-0.008364	-0.169367	0.085217
DIFBNEER	0.022532	0.002656	-0.177798	-0.319690	0.010686
DIFCOI	0.004628	-0.184724	0.248466	0.060178	-0.215341
DIFCOP	-0.006882	-0.156601	0.258983	0.064043	-0.187083
DIFGFI	0.187475	-0.315320	-0.172422	0.148604	-0.360745
DIFIBC_BR	-0.121525	-0.096112	0.065750	0.343207	-0.161135
DIFLNBAPI	0.196774	-0.105863	-0.316065	-0.027400	-0.098456
DIFLNBAPROD	-0.143723	-0.101335	-0.334049	-0.116251	-0.102741
DIFLNBFEXP	-0.138136	-0.013541	0.022087	-0.355794	0.002809
DIFLNBFIMP	-0.044411	-0.014482	0.339245	-0.016253	-0.000535
DIFLNBER	-0.100255	0.081826	0.011962	-0.154658	0.101089
DIFLNBNEER	0.014462	0.003529	-0.156098	-0.314264	0.014995
DIFLNCOI	-0.079317	-0.174070	0.180983	0.079889	-0.212160
DIFLNCOP	-0.087507	-0.154763	0.188737	0.084240	-0.192091
DIFLNGFI	0.203008	-0.321149	-0.181578	0.142222	-0.364991
DIFLNIBC_BR	-0.129648	-0.098030	0.066285	0.339041	-0.161750

Note. The statistics were done by the software Eviews v.12
The raw data can be found at Appendix A

Table B - 5

BRAZILIAN DATA CORRELOGRAM B

	DIFBENINF	DIFBER	DIFBNEER	DIFCOI	DIFCOP
BF_BINF	-0.058231	-0.070016	0.022532	0.004628	-0.006882
BIR	-0.045754	0.066639	0.002656	-0.184724	-0.156601
BENINF	0.653499	-0.008364	-0.177798	0.248466	0.258983
IBC_BR	-0.034862	-0.169367	-0.319690	0.060178	0.064043
LNBIR	-0.031727	0.085217	0.010686	-0.215341	-0.187083
DIFBENINF	1.000000	-0.021546	-0.151808	0.096801	0.091912
DIFBER	-0.021546	1.000000	0.648396	-0.340545	-0.330267
DIFBNEER	-0.151808	0.648396	1.000000	-0.343558	-0.338851
DIFCOI	0.096801	-0.340545	-0.343558	1.000000	0.998191
DIFCOP	0.091912	-0.330267	-0.338851	0.998191	1.000000
DIFGFI	-0.043538	-0.311703	-0.180054	0.399507	0.382354
DIFIBC_BR	-0.003782	-0.348119	-0.423057	0.439728	0.434810
DIFLNBAPI	-0.294827	0.284069	0.423262	-0.337069	-0.340965
DIFLNBAPROD	-0.043911	0.102374	0.080129	0.185	0.181057
DIFLNBFEXP	0.198799	0.143108	0.174385	-0.112581	-0.105916
DIFLNBFIMP	-0.022256	0.003723	-0.088442	0.027447	0.024405
DIFLNBER	0.004946	0.987909	0.630892	-0.333093	-0.321289
DIFLNBNEER	-0.121974	0.668624	0.994208	-0.356057	-0.352267

BRAZILIAN DATA CORRELOGRAM B

	DIFBENINF	DIFBER	DIFBNEER	DIFCOI	DIFCOP
DIFLNCOI	0.073297	-0.379037	-0.389130	0.939089	0.938682
DIFLNCOP	0.070018	-0.369842	-0.382960	0.939931	0.942075
DIFLNGFI	-0.040120	-0.322161	-0.198666	0.436042	0.418518
DIFLNIBC_BR	0.000206	-0.341069	-0.422727	0.445695	0.440867

Note. The statistics were done by the software Eviews v.12
The raw data can be found at Appendix A

Table B - 6

BRAZILIAN DATA CORRELOGRAM C

	DIFGFI	DIFIBC_BR	DIFLNBAPI	DIFLNBAPROD	DIFLNBAPROD	DIFLNIBC_BR
BF_BINF	0.187475	-0.121525	0.196774	-0.143723	-0.143723	-0.087507
BIR	-0.315320	-0.096112	-0.105863	-0.101335	-0.101335	-0.154763
BENINF	-0.172422	0.065750	-0.316065	-0.334049	-0.334049	0.188737
IBC_BR	0.148604	0.343207	-0.027400	-0.116251	-0.116251	0.084240
LNBIR	-0.360745	-0.161135	-0.098456	-0.102741	-0.102741	-0.192091
DIFBENINF	-0.043538	-0.003782	-0.294827	-0.043911	-0.043911	0.070018
DIFBER	-0.311703	-0.348119	0.284069	0.102374	0.102374	-0.369842
DIFBNEER	-0.180054	-0.423057	0.423262	0.080129	0.080129	-0.382960
DIFCOI	0.399507	0.439728	-0.337069	0.185025	0.185025	0.939931
DIFCOP	0.382354	0.434810	-0.340965	0.181057	0.181057	0.942075
DIFGFI	1.000000	0.220828	0.055407	0.066965	0.066965	0.407588
DIFIBC_BR	0.220828	1.000000	-0.076838	0.127078	0.127078	0.620958
DIFLNBAPI	0.055407	-0.076838	1.000000	-0.056202	-0.056202	-0.323245
DIFLNBAPROD	0.066965	0.127078	-0.056202	1.000000	1.000000	0.175872
DIFLNBFEXP	0.040392	-0.459951	0.115897	0.045762	0.045762	-0.145891
DIFLNBFIMP	-0.254882	-0.114780	-0.072915	-0.088473	-0.088473	-0.087565
DIFLNBER	-	-0.325885	0.284356	0.123284	0.123284	-0.350839

BRAZILIAN DATA CORRELOGRAM C

	DIFGFI	DIFIBC_BR	DIFLNBAPI	DIFLNBAPROD	DIFLNBAPROD	DIFLNIBC_BR
	0.328882					
DIFLNBNEER	-0.202489	-0.426326	0.415221	0.090988	0.090988	-0.396474
DIFLNCOI	0.419953	0.630989	-0.316872	0.178858	0.178858	0.998999
DIFLNCOP	0.407588	0.620958	-0.323245	0.175872	0.175872	1.000000
DIFLNGFI	0.992988	0.245705	0.063776	0.070424	0.070424	0.448198
DIFLNIBC_BR	0.226524	0.998892	-0.076701	0.127364	0.127364	0.632296

Note. The statistics were done by the software Eviews v.12
The raw data can be found at Appendix A

Table B - 7

CORRELOGRAM D

	DIFLNBFIMP	DIFLNBER	DIFLNBNEER	DIFLNCOI	DIFLNCOP	DIFLNGFI
BF_BINF	-0.143723	-0.138136	-0.044411	-0.100255	0.014462	-0.079317
BIR	-0.101335	-0.013541	-0.014482	0.081826	0.003529	-0.174070
BENINF	-0.334049	0.022087	0.339245	0.011962	-0.156098	0.180983
IBC_BR	-0.116251	-0.355794	-0.016253	-0.154658	-0.314264	0.079889
LNBIR	-0.102741	0.002809	-0.000535	0.101089	0.014995	-0.212160
DIFBENINF	-0.043911	0.198799	-0.022256	0.004946	-0.121974	0.073297
DIFBER	0.102374	0.143108	0.003723	0.987909	0.668624	-0.379037
DIFBNEER	0.080129	0.174385	-0.088442	0.630892	0.994208	-0.389130
DIFCOI	0.185025	-0.112581	0.027447	-0.333093	-0.356057	0.939089
DIFCOP	0.181057	-0.105916	0.024405	-0.321289	-0.352267	0.938682
DIFGFI	0.066965	0.040392	-0.254882	-0.328882	-0.202489	0.419953
DIFIBC_BR	0.127078	-0.459951	-0.114780	-0.325885	-0.426326	0.630989
DIFLNBAPI	-0.056202	0.115897	-0.072915	0.284356	0.415221	-0.316872
DIFLNBAPROD	1.000000	0.045762	-0.088473	0.123284	0.090988	0.178858
DIFLNBFEXP	0.045762	1.000000	0.131958	0.161327	0.174622	-0.152421
DIFLNBFIMP	-0.088473	0.131958	1.000000	-0.002710	-0.094908	-0.087760
DIFLNBER	0.123284	0.161327	-0.002710	1.000000	0.661152	-0.361016
DIFLNBNEER	0.090988	0.174622	-0.094908	0.661152	1.000000	-0.402121
DIFLNCOI	0.178858	-0.152421	-0.087760	-0.361016	-0.402121	1.000000
DIFLNCOP	0.175872	-0.145891	-0.087565	-0.350839	-0.396474	0.998999
DIFLNGFI	0.070424	0.019639	-0.264144	-0.342479	-0.222807	0.461001
DIFLNIBC_BR	0.127364	-0.450396	-0.131709	-0.318768	-0.425327	0.642371

Note. The statistics were done by the software Eviews v.12
The raw data can be found at Appendix A

Table B - 8

Residuals Brazil MODEL 1

Date: 10/08/22 Time: 14:09
Sample (adjusted): 2018M09 2021M12
Q-statistic probabilities adjusted for 2 dynamic regressors

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th></tr>
<tr><td>. | . |</td><td>. | . |</td><td>1</td><td>0.029</td><td>0.029</td><td>0.0371</td><td>0.847</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>2</td><td>-0.100</td><td>-0.101</td><td>0.4815</td><td>0.786</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>3</td><td>0.028</td><td>0.034</td><td>0.5164</td><td>0.915</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>-0.123</td><td>-0.137</td><td>1.2185</td><td>0.875</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>5</td><td>-0.180</td><td>-0.169</td><td>2.7785</td><td>0.734</td></tr>
</table>

.*| . |	**| . |	6	-0.178	-0.209	4.3481	0.630
**| . |	**| . |	7	-0.215	-0.273	6.6969	0.461
. |*. |	. | . |	8	0.111	0.040	7.3409	0.500
. |*. |	. | . |	9	0.128	0.029	8.2353	0.511
.*| . |	.*| . |	10	-0.080	-0.154	8.5893	0.571
. |*. |	. | . |	11	0.098	-0.031	9.1506	0.608
. |*. |	. | . |	12	0.165	0.036	10.791	0.547
. | . |	.*| . |	13	-0.041	-0.076	10.897	0.619
. |*. |	. |*. |	14	0.106	0.131	11.622	0.637
**| . |	**| . |	15	-0.297	-0.329	17.544	0.287
.*| . |	.*| . |	16	-0.105	-0.076	18.313	0.306
. | . |	.*| . |	17	0.003	-0.142	18.314	0.369
.*| . |	.*| . |	18	-0.122	-0.122	19.453	0.364
. | . |	.*| . |	19	-0.041	-0.096	19.585	0.420
. |*. |	. | . |	20	0.206	0.003	23.152	0.281

Note. The statistics were done by the software Eviews v.12

Table B - 9

BRAZIL MODEL 1. Breusch-Godfrey Serial Correlation LM Test:

Null hypothesis: No serial correlation at up to 8 lags

F-statistic	0.946926	Prob. F(8,20)	0.5018
Obs*R-squared	10.98864	Prob. Chi-Square(8)	0.2023

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 10/08/22 Time: 17:18
Sample: 2018M09 2021M12
Included observations: 40
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BF_BINF(-1)	-0.382749	1.209396	-0.316479	0.7549
BF_BINF(-2)	0.158846	0.370274	0.428996	0.6725
DIFLNBAPROD	8.375828	15.88848	0.527164	0.6039
DIFLNBAPROD(-1)	4.041963	22.79535	0.177315	0.8610
DIFLNBAPROD(-2)	-6.449920	36.68637	-0.175812	0.8622
DIFLNBAPROD(-3)	5.272679	24.14362	0.218388	0.8293
DIFLNBAPROD(-4)	3.362599	19.34896	0.173787	0.8638
DIFLNBAPROD(-5)	-6.199377	39.09589	-0.158568	0.8756
DIFLNBAPROD(-6)	4.157091	17.35684	0.239507	0.8131
DIFLNBAPROD(-7)	-16.51174	59.67251	-0.276706	0.7848
BIR	-0.129388	0.227794	-0.568005	0.5764
C	0.767539	1.807671	0.424601	0.6757
RESID(-1)	0.175690	1.237055	0.142023	0.8885
RESID(-2)	-0.268397	0.562995	-0.476731	0.6387
RESID(-3)	-0.191381	0.272587	-0.702091	0.4907
RESID(-4)	-0.267143	0.254969	-1.047745	0.3073
RESID(-5)	-0.319354	0.227826	-1.401747	0.1763
RESID(-6)	-0.391841	0.239537	-1.635824	0.1175
RESID(-7)	-0.460947	0.247356	-1.863495	0.0771
RESID(-8)	-0.101460	0.261849	-0.387476	0.7025

R-squared	0.274716	Mean dependent var	9.99E-17
Adjusted R-squared	-0.414304	S.D. dependent var	0.561916
S.E. of regression	0.668256	Akaike info criterion	2.338562
Sum squared resid	8.931319	Schwarz criterion	3.183001
Log likelihood	-26.77123	Hannan-Quinn criter.	2.643884
F-statistic	0.398705	Durbin-Watson stat	1.920786

Prob(F-statistic)	0.974960

Table B - 10

Brazil Model 1. Heteroskedasticity Test: Breusch-Pagan-Godfrey

Null hypothesis: Homoskedasticity

F-statistic	0.957972	Prob. F(11,28)	0.5041
Obs*R-squared	10.93754	Prob. Chi-Square(11)	0.4485
Scaled explained SS	4.764450	Prob. Chi-Square(11)	0.9420

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/08/22 Time: 17:19
Sample: 2018M09 2021M12
Included observations: 40

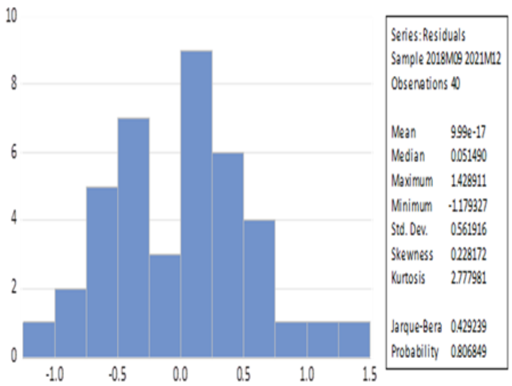
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.050620	0.299557	0.168982	0.8670
BF_BINF(-1)	0.300247	0.112803	2.661687	0.0127
BF_BINF(-2)	-0.110807	0.100895	-1.098243	0.2815
DIFLNBAPROD	3.905068	9.455124	0.413011	0.6827
DIFLNBAPROD(-1)	3.090567	9.635653	0.320743	0.7508
DIFLNBAPROD(-2)	12.84594	10.09116	1.272990	0.2135
DIFLNBAPROD(-3)	2.887894	10.62841	0.271715	0.7878
DIFLNBAPROD(-4)	-9.553914	11.70344	-0.816334	0.4212
DIFLNBAPROD(-5)	15.19729	9.880851	1.538055	0.1353
DIFLNBAPROD(-6)	-12.19585	9.794515	-1.245171	0.2234
DIFLNBAPROD(-7)	11.23713	10.76185	1.044164	0.3053
BIR	0.026529	0.051775	0.512389	0.6124

R-squared	0.273439	Mean dependent var	0.307856
Adjusted R-squared	-0.011996	S.D. dependent var	0.415727
S.E. of regression	0.418214	Akaike info criterion	1.337676
Sum squared resid	4.897274	Schwarz criterion	1.844340
Log likelihood	-14.75353	Hannan-Quinn criter.	1.520870
F-statistic	0.957972	Durbin-Watson stat	1.699445
Prob(F-statistic)	0.504051		

Table B - 11

Brazilian Model 1 Test for multicollinearity and residuals test of normality and stability.

a)



b)

Variance Inflation Factors
Date: 10/08/22 Time: 17:33
Sample: 2018M01 2021M12
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
BF_BINF(-1)	0.031996	3.438151	2.068676
BF_BINF(-2)	0.025597	2.751309	1.662091
DIFLNBAPROD	224.7955	1.145872	1.140310
DIFLNBAPROD(-1)	233.4616	1.173992	1.169502
DIFLNBAPROD(-2)	256.0562	1.292995	1.287005
DIFLNBAPROD(-3)	284.0467	1.495028	1.481779
DIFLNBAPROD(-4)	344.4134	1.418924	1.417063
DIFLNBAPROD(-5)	245.4946	1.263077	1.255546
DIFLNBAPROD(-6)	241.2231	1.254666	1.240208
DIFLNBAPROD(-7)	291.2237	1.479559	1.448523
BIR	0.006741	16.14097	2.381296
C	0.225639	20.52220	NA

c)

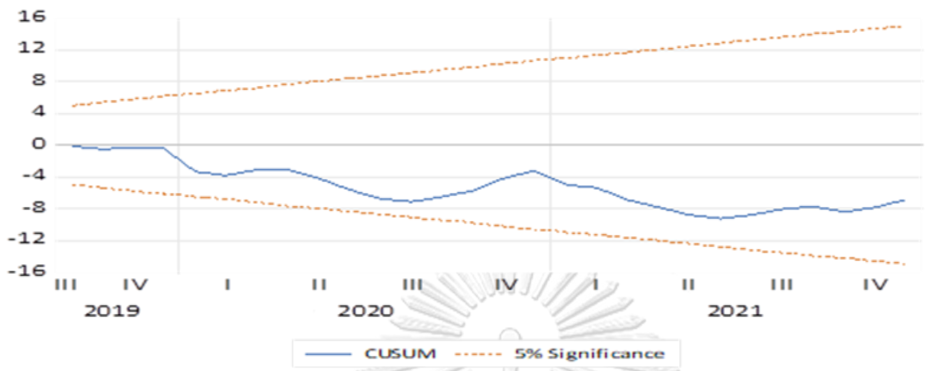


Table B - 12

Brazilian Model 1. ARDL Long Run Form and Bounds Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(BF_BINF)
Selected Model: ARDL(2, 7)
Case 3: Unrestricted Constant and No Trend
Date: 10/10/22 Time: 16:01
Sample: 2018M01 2021M12
Included observations: 41

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	375.2814	398.7609	0.941119	0.3544
BF_BINF(-1)*	-0.683664	0.170698	-4.005106	0.0004
LNBAPROD(-1)	-17.84413	19.02107	-0.938124	0.3559
D(BF_BINF(-1))	0.155120	0.150215	1.032652	0.3103
D(LNBAPROD)	-23.37545	20.17410	-1.158686	0.2560
D(LNBAPROD(-1))	-19.48100	15.67361	-1.242918	0.2239
D(LNBAPROD(-2))	23.86479	15.93327	1.497796	0.1450
D(LNBAPROD(-3))	0.812604	16.74061	0.048541	0.9616
D(LNBAPROD(-4))	-24.89882	14.87199	-1.674209	0.1048
D(LNBAPROD(-5))	15.37655	15.28406	1.006051	0.3227
D(LNBAPROD(-6))	-48.90473	15.13161	-3.231959	0.0031
BIR	-0.307058	0.195613	-1.569717	0.1273

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFLNBAPROD	-26.10072	29.21480	-0.893407	0.3790

EC = BF_BINF - (-26.1007*LNBAPROD)

F-Bounds Test Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)

		Asymptotic: n=1000		
F-statistic k	8.936234 1	10% 5% 2.5% 1%	4.04 4.94 5.77 6.84	4.78 5.73 6.68 7.84
		Finite Sample: n=45		
Actual Sample Size	41	10% 5% 1%	4.225 5.235 7.74	5.02 6.135 8.65
		Finite Sample: n=40		
t-Bounds Test	Null Hypothesis: No levels relationship			
Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-4.005106	10% 5% 2.5% 1%	-2.57 -2.86 -3.13 -3.43	-2.91 -3.22 -3.5 -3.82

Table B - 13

Brazil Model 2b . Residuals

Date: 10/11/22 Time: 13:24
Sample (adjusted): 2018M05 2021M12
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation	AC PAC Q-Stat	Prob*
. | . |	. | . |	10.0190.0190.0177	0.894
. | . |	. | . |	20.0570.0570.1767	0.915
		- -	
. | . |	. | . |	30.0250.0270.2078	0.976
. |*. |	. |*. |	40.0980.0960.6961	0.952
. | . |	. | . |	50.0300.0300.7441	0.980
. | . |	. | . |	60.0240.0110.7745	0.993
		- -	
**| . |	**| . |	70.2980.3015.6204	0.585
		- -	
.*| . |	.*| . |	80.0910.0986.0862	0.638
. |** |	. |** |	90.2230.2858.9627	0.441
. | . |	. | . |	100.0460.0509.0903	0.524
		- -	
. | . |	. | . |	110.0340.0409.1595	0.607
		- -	
. | . |	. | . |	120.0340.0099.2330	0.683
. |*. |	. |*. |	130.0770.0749.6163	0.725
		-	
. | . |	. | . |	140.0690.0449.9401	0.767
		- -	
.*| . |	**| . |	150.0950.22810.570	0.782
		- -	
**| . |	.*| . |	160.2450.13114.916	0.531
		- -	
**| . |	.*| . |	170.2680.19720.305	0.259
. |*. |	. |*. |	180.0880.07820.912	0.284
		-	
. | . |	. | . |	190.0110.04120.922	0.341
		- -	
.*| . |	.*| . |	200.1340.08422.429	0.318

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.002742	Prob. F(7,36)	0.4454
Obs*R-squared	7.179226	Prob. Chi-Square(7)	0.4105
Scaled explained SS	5.651038	Prob. Chi-Square(7)	0.581

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/11/22 Time: 13:26
Sample: 2018M05 2021M12
Included observations: 44

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.268245	0.099117	2.706358	0.0103
BF_BINF(-1)	0.041684	0.107939	0.386177	0.701
DIFLNBAPI	-0.647432	2.797166	-0.231460	0.818
DIFLNBAPI(-1)	4.313570	2.966992	1.453853	0.154
DIFLNBAPI(-2)	-3.791949	3.043379	-1.245966	0.220
DIFLNBAPI(-3)	3.580797	2.640109	1.356306	0.183

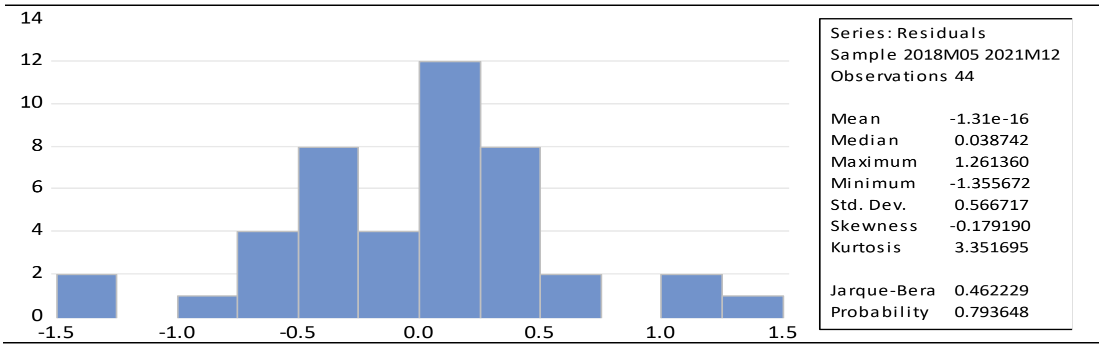


Table B - 14

Brazil Model 2b. Multicollinearity and stability test

Variance Inflation Factors
Date: 10/11/22 Time: 13:26
Sample: 2018M01 2021M12
Included observations: 44

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
BF_BINF(-1)	0.018862	2.532420	1.542714
DIFLNBAPI	12.66681	1.345588	1.320965
DIFLNBAPI(-1)	14.25160	1.504542	1.482407
DIFLNBAPI(-2)	14.99488	1.675481	1.636099
DIFLNBAPI(-3)	11.28429	1.225201	1.179848
DIFBENINF	0.001438	1.803681	1.803680
DIFBENINF(-1)	0.001554	1.946712	1.946626
C	0.015905	1.824219	NA

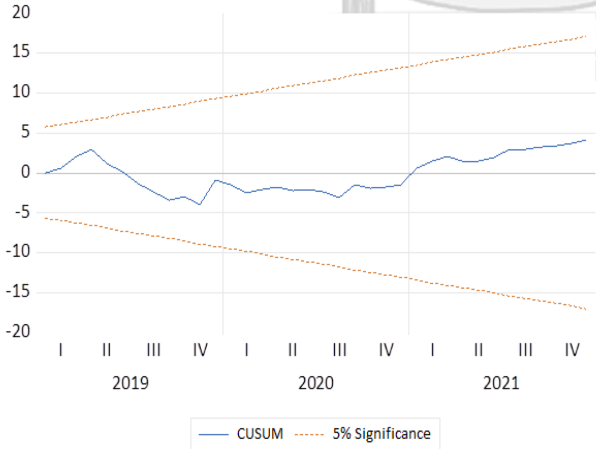


Table B - 15

Brazil Model 2b. Long Run Form and Bound Test

Brazil Model 2b. Long Run Form and Bound Test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(BF_BINF)
Selected Model: ARDL(1, 2, 2)
Case 3: Unrestricted Constant and No Trend
Date: 10/12/22 Time: 10:24
Sample: 2018M01 2021M12
Included observations: 46

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNBAPI	2.930650	1.216465	2.409152	0.0209
BENINF	-0.062950	0.080135	-0.785545	0.4370

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Pr
C	-10.20317	4.839056	-2.108504	0.
BF_BINF(-1)*	-0.784046	0.130695	-5.999032	0.
LNBAPI(-1)	2.297764	1.052258	2.183650	0.
BENINF(-1)	-0.049356	0.062750	-0.786541	0.4
D(LNBAPI)	4.755236	3.534444	1.345398	0.
D(LNBAPI(-1))	12.51106	3.554005	3.520271	0.
D(BENINF)	-0.003846	0.043667	-0.088084	0.
D(BENINF(-1))	0.096501	0.039957	2.415114	0.

EC = BF_BINF - (2.9306*LNBAPI -0.0629*BENINF)

F-Bounds Test — Null Hypothesis: No levels relationship

Test statistic	value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	12.17903	10%	3.17	4.14
k	2	5%	3.79	4.85
		2.5%	4.41	5.52
		1%	5.15	6.36
			Finite Sample: n=50	
Actual Sample Size	46	10%	3.333	4.313
		5%	4.07	5.19
		1%	5.817	7.303
			Finite Sample: n=45	
		10%	3.33	4.347
		5%	4.083	5.207
		1%	5.92	7.197

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-5.999032	10%	-2.57	-3.21
		5%	-2.86	-3.53
		2.5%	-3.13	-3.8
		1%	-3.43	-4.1

Table B - 16

Brazilian model 2a. Residuals

Brazilian model 2a. Residuals

Date: 10/13/22 Time: 14:59
Sample (adjusted): 2018M03 2021M12
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.046	0.046	0.1018	0.750
		2	-0.133	-0.135	0.9838	0.611
		3	0.012	0.025	0.9908	0.803
		4	0.177	0.160	2.6371	0.620
		5	0.114	0.106	3.3327	0.649
		6	0.081	0.120	3.6953	0.718
		7	-0.174	-0.171	5.4048	0.611
		8	-0.094	-0.100	5.9174	0.656
		9	0.185	0.122	7.9563	0.539
		10	-0.011	-0.085	7.9635	0.632
		11	-0.100	-0.019	8.5893	0.660
		12	0.021	0.071	8.6167	0.735
		13	0.156	0.158	10.236	0.675
		14	0.030	0.016	10.299	0.740
		15	-0.105	-0.138	11.088	0.746
		16	-0.106	-0.077	11.911	0.750
		17	-0.102	-0.177	12.698	0.756
		18	0.276	0.230	18.708	0.410
		19	-0.023	-0.039	18.750	0.473
		20	-0.193	-0.028	21.900	0.346

*Probabilities may not be valid for this equation specification.

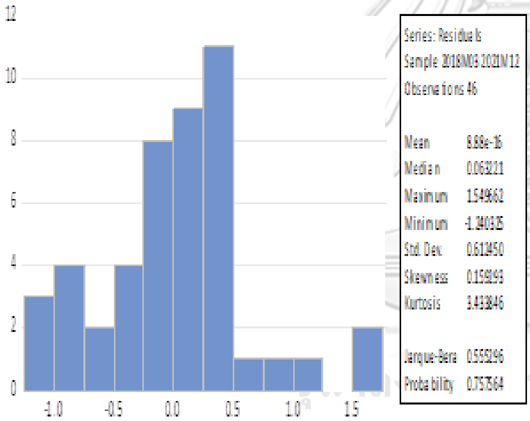
Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 4 lags

F-statistic	0.455647	Prob. F(4,35)	0.7676
Obs*R-squared	2.276836	Prob. Chi-Square(4)	0.6850

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 10/13/22 Time: 15:00
Sample: 2018M03 2021M12
Included observations: 46
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BF_BINF(-1)	0.009636	0.210320	0.045816	0.9637
LNBF_BEXP	0.014295	0.479368	0.029821	0.9764
DIFLNBAPI	0.067290	3.803495	0.017692	0.9860
DIFLNBAPI(-1)	0.138359	4.020429	0.034414	0.9727
DIFBENINF	-0.012627	0.043272	-0.291803	0.7722
DIFBENINF(-1)	-0.009054	0.040699	-0.222475	0.8252
C	-0.229459	7.601202	-0.030187	0.9761
RESID(-1)	0.051531	0.268714	0.191768	0.8490
RESID(-2)	-0.127278	0.186238	-0.683416	0.4988
RESID(-3)	0.019449	0.177542	0.109544	0.9134
RESID(-4)	0.169797	0.174365	0.973800	0.3368

R-squared	0.049496	Mean dependent var	8.88E-16
Adjusted R-squared	-0.222076	S.D. dependent var	0.612450
S.E. of regression	0.677049	Akaike info criterion	2.262821
Sum squared resid	16.04383	Schwarz criterion	2.700105
Log likelihood	-41.04488	Hannan-Quinn criter.	2.426630
F-statistic	0.182259	Durbin-Watson stat	1.961811
Prob(F-statistic)	0.996538		



Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.859359	Prob. F(6,39)	0.5330
Obs*R-squared	5.371463	Prob. Chi-Square(6)	0.4971
Scaled explained SS	4.698608	Prob. Chi-Square(6)	0.5830

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/13/22 Time: 15:01
Sample: 2018M03 2021M12
Included observations: 46

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.461935	6.286920	0.550657	0.5850
BF_BINF(-1)	0.015269	0.110547	0.138120	0.8909
LNBF_BEXP	-0.198745	0.397886	-0.499503	0.6202
DIFLNBAPI	0.240061	3.219406	0.074567	0.9409
DIFLNBAPI(-1)	4.169682	3.245072	1.284928	0.2064
DIFBENINF	0.017712	0.035826	0.494395	0.6238
DIFBENINF(-1)	0.064778	0.033933	1.909013	0.0636

R-squared	0.116771	Mean dependent var	0.366941
Adjusted R-squared	-0.019110	S.D. dependent var	0.578783
S.E. of regression	0.584287	Akaike info criterion	1.902420
Sum squared resid	13.31427	Schwarz criterion	2.180691
Log likelihood	-36.75565	Hannan-Quinn criter.	2.006662
F-statistic	0.859359	Durbin-Watson stat	1.607395
Prob(F-statistic)	0.533036		

Table B- 18

Brazilian Model 2a. Attempts.

a)

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/13/22 Time: 05:45
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNGFI DIFLNCOI DIFLNBAPI DIFBENINF
Fixed regressors: C
Number of models evaluated: 2500
Selected Model: ARDL(1, 1, 0, 1, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.310410	0.120472	2.576615	0.0141
DIFLNGFI	5.641189	3.971026	1.420587	0.1638
DIFLNGFI(-1)	5.105589	3.670681	1.390911	0.1726
DIFLNCOI	-1.464526	0.851650	-1.719634	0.0939
DIFLNBAPI	3.333068	3.828340	0.870630	0.3896
DIFLNBAPI(-1)	12.89734	3.551074	3.631953	0.0008
DIFBENINF	0.009448	0.038922	0.242729	0.8096
DIFBENINF(-1)	0.084582	0.036620	2.309752	0.0266
C	0.324910	0.123792	2.624645	0.0125

R-squared	0.522999	Mean dependent var	0.663696
Adjusted R-squared	0.419864	S.D. dependent var	0.842642
S.E. of regression	0.641813	Akaike info criterion	2.124540
Sum squared resid	15.24116	Schwarz criterion	2.482317
Log likelihood	-39.86442	Hannan-Quinn criter.	2.258565
F-statistic	5.071002	Durbin-Watson stat	1.898762
Prob(F-statistic)	0.000267		

*Note: p-values and any subsequent tests do not account for model selection.

b)

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/13/22 Time: 05:57
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNGFI DIFLNCOI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.383543	0.137274	2.793993	0.0077
DIFLNGFI	8.115809	4.532512	1.790576	0.0804
DIFLNCOI	-1.677901	0.938574	-1.787714	0.0809
C	0.356442	0.143598	2.482221	0.0170

R-squared	0.220661	Mean dependent var	0.642553
Adjusted R-squared	0.166289	S.D. dependent var	0.845943
S.E. of regression	0.772412	Akaike info criterion	2.402668
Sum squared resid	25.65467	Schwarz criterion	2.560127
Log likelihood	-52.46269	Hannan-Quinn criter.	2.461921
F-statistic	4.058321	Durbin-Watson stat	1.972946
Prob(F-statistic)	0.012616		

*Note: p-values and any subsequent tests do not account for model selection.

c)

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/13/22 Time: 06:48
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): BER DIFLNBAPI DIFBENINF
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 3, 1, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.292306	0.124962	2.339161	0.0252
BER	-0.227676	0.474821	-0.479499	0.6346
BER(-1)	0.629693	0.690279	0.912229	0.3679
BER(-2)	-1.286822	0.702876	-1.830795	0.0757
BER(-3)	1.068976	0.464526	2.301221	0.0275
DIFLNBAPI	4.882574	3.779158	1.291974	0.2048
DIFLNBAPI(-1)	14.05441	3.725460	3.772530	0.0006
DIFBENINF	0.045178	0.039873	1.133043	0.2649
DIFBENINF(-1)	0.098085	0.036093	2.717572	0.0102
C	-0.390582	0.586958	-0.665434	0.5101

R-squared	0.574372	Mean dependent var	0.680000
Adjusted R-squared	0.464925	S.D. dependent var	0.844794
S.E. of regression	0.617957	Akaike info criterion	2.068335
Sum squared resid	13.36548	Schwarz criterion	2.469815
Log likelihood	-36.53753	Hannan-Quinn criter.	2.218002
F-statistic	5.247938	Durbin-Watson stat	1.986283
Prob(F-statistic)	0.000156		

*Note: p-values and any subsequent tests do not account for model selection.

d)

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/13/22 Time: 06:31
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFBER DIFLNBAPI DIFBENINF
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 2, 1, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.352874	0.118952	2.966513	0.0053
DIFBER	-0.406421	0.463840	-0.876211	0.3867
DIFBER(-1)	0.297030	0.485447	0.611869	0.5445
DIFBER(-2)	-1.024228	0.469765	-2.180298	0.0359
DIFLNBAPI	5.991921	3.746842	1.599192	0.1185
DIFLNBAPI(-1)	13.48137	3.753773	3.591419	0.0010
DIFBENINF	0.046964	0.040397	1.162572	0.2527
DIFBENINF(-1)	0.096324	0.036563	2.634450	0.0123
C	0.418411	0.126244	3.314302	0.0021

R-squared	0.550182	Mean dependent var	0.680000
Adjusted R-squared	0.450222	S.D. dependent var	0.844794
S.E. of regression	0.626390	Akaike info criterion	2.079169
Sum squared resid	14.12511	Schwarz criterion	2.440501
Log likelihood	-37.78129	Hannan-Quinn criter.	2.213870
F-statistic	5.504036	Durbin-Watson stat	2.004667
Prob(F-statistic)	0.000144		

*Note: p-values and any subsequent tests do not account for model selection.

Table B - 17

Brazilian Model 2a. Coefficient diagnostics and stability

ARDL Long Run Form and Bounds Test
Dependent Variable: D(BF_BINF)
Selected Model: ARDL(1, 0, 1, 1)
Case 3: Unrestricted Constant and No Trend
Date: 10/13/22 Time: 15:17
Sample: 2018M01 2021M12
Included observations: 46

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	8.195527	7.078748	1.157765	0.2540
BF_BINF(-1)*	-0.693768	0.124470	-5.573790	0.0000
LNBF_BEXP**	-0.496470	0.447999	-1.108194	0.2746
DIFLNBAPI(-1)	18.38195	4.272880	4.302004	0.0001
DIFBENINF(-1)	0.115433	0.068964	1.673825	0.1022
D(DIFLNBAPI)	4.612862	3.624885	1.272554	0.2107
D(DIFBENINF)	0.022492	0.040338	0.557600	0.5803

* p-value incompatible with t-Bounds distribution.
** Variable interpreted as Z = Z(-1) + D(Z).

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LNBF_BEXP	-0.715614	0.630132	-1.135657	0.2630
DIFLNBAPI	26.49582	7.767753	3.411001	0.0015
DIFBENINF	0.166386	0.102588	1.621891	0.1129

EC = BF_BINF - (-0.7156*LNBF_BEXP + 26.4958*DIFLNBAPI + 0.1664 *DIFBENINF)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	12.67826	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
		Finite Sample: n=50		
Actual Sample Size	46	10%	2.873	3.973
		5%	3.5	4.7
		1%	4.865	6.36
		Finite Sample: n=45		
		10%	2.893	3.983
		5%	3.535	4.733
		1%	4.983	6.423

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-5.573790	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

Variance Inflation Factors
Date: 10/13/22 Time: 15:06
Sample: 2018M01 2021M12
Included observations: 46

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
BF_BINF(-1)	0.015493	1.847731	1.176933
LNBF_BEXP	0.200703	5303.129	1.135597
DIFLNBAPI	13.13979	1.309309	1.275377
DIFLNBAPI(-1)	13.35013	1.327241	1.293787
DIFBENINF	0.001627	1.809708	1.809680
DIFBENINF(-1)	0.001460	1.663714	1.661939
C	50.10868	5325.754	NA

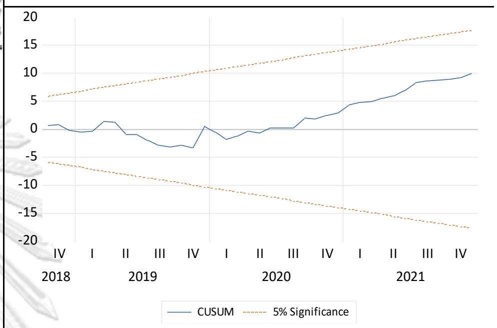


Table B - 18

Brazil Model 1 Attemps

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/14/22 Time: 18:31
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNBAPROD DIFLNBER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 2, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.475818	0.134979	3.525120	0.0011
DIFLNBAPROD	-12.09224	13.88921	-0.870621	0.3896
DIFLNBAPROD(-1)	-15.66598	14.35266	-1.091503	0.2821
DIFLNBAPROD(-2)	35.62105	14.26296	2.497451	0.0171
DIFLNBER	-2.039064	2.378706	-0.857216	0.3968
DIFLNBER(-1)	3.160257	2.367597	1.334796	0.1901
DIFLNBER(-2)	-5.043169	2.390288	-2.109858	0.0417
C	0.409849	0.146865	2.790644	0.0083

R-squared	0.373601	Mean dependent var	0.680000
Adjusted R-squared	0.255093	S.D. dependent var	0.844794
S.E. of regression	0.729125	Akaike info criterion	2.365868
Sum squared resid	19.67007	Schwarz criterion	2.687053
Log likelihood	-45.23203	Hannan-Quinn criter.	2.485603
F-statistic	3.152535	Durbin-Watson stat	1.838495
Prob(F-statistic)	0.010254		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/14/22 Time: 19:38
Sample (adjusted): 2018M09 2021M12
Included observations: 40 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): DIFLNBAPROD LNBER
Fixed regressors: C
Number of models evaluated: 324
Selected Model: ARDL(2, 7, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.670328	0.178151	3.762688	0.0008
BF_BINF(-2)	-0.272727	0.166791	-1.635139	0.1132
DIFLNBAPROD	-5.072840	15.91174	-0.318811	0.7522
DIFLNBAPROD(-1)	-15.76293	15.48776	-1.017767	0.3175
DIFLNBAPROD(-2)	33.13725	15.64210	2.118465	0.0431
DIFLNBAPROD(-3)	8.089663	16.13325	0.501428	0.6200
DIFLNBAPROD(-4)	-23.16171	18.01296	-1.285836	0.2090
DIFLNBAPROD(-5)	25.83183	15.34576	1.683320	0.1034
DIFLNBAPROD(-6)	-46.55955	15.14423	-3.074408	0.0047
DIFLNBAPROD(-7)	26.66975	16.57073	1.609449	0.1187
LNBER	0.802124	0.783831	1.023339	0.3149
C	-0.796418	1.162238	-0.685246	0.4988

R-squared	0.527927	Mean dependent var	0.718000
Adjusted R-squared	0.342470	S.D. dependent var	0.834350
S.E. of regression	0.676559	Akaike info criterion	2.299732
Sum squared resid	12.81651	Schwarz criterion	2.806396
Log likelihood	-33.99464	Hannan-Quinn criter.	2.482926
F-statistic	2.846625	Durbin-Watson stat	2.018735
Prob(F-statistic)	0.012432		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/14/22 Time: 19:47
Sample (adjusted): 2018M09 2021M12
Included observations: 40 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (8 lags, automatic): DIFLNBAPROD DIFLNBER
Fixed regressors: C
Number of models evaluated: 324
Selected Model: ARDL(2, 0, 7)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.643824	0.159420	4.038530	0.0004
BF_BINF(-2)	-0.176975	0.160980	-1.099357	0.2810
DIFLNBAPROD	-17.10383	17.76322	-0.962879	0.3439
DIFLNBER	-3.111686	2.544139	-1.223080	0.2315
DIFLNBER(-1)	3.312601	2.373965	1.395388	0.1739
DIFLNBER(-2)	-4.673589	2.433698	-1.920365	0.0651
DIFLNBER(-3)	2.582822	2.459811	1.050008	0.3027
DIFLNBER(-4)	-0.408585	2.372840	-0.172192	0.8645
DIFLNBER(-5)	1.371282	2.639663	0.519491	0.6075
DIFLNBER(-6)	-1.185023	2.312780	-0.512380	0.6124
DIFLNBER(-7)	7.301419	2.351500	3.105005	0.0043
C	0.308713	0.185951	1.660188	0.1080

R-squared	0.503242	Mean dependent var	0.718000
Adjusted R-squared	0.308088	S.D. dependent var	0.834350

Dependent Variable: BF_BINF
Method: ARDL
Date: 10/14/22 Time: 19:50
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNBAPROD LNBER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 2, 3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
BF_BINF(-1)	0.428687	0.141072	3.038791	0.0044
DIFLNBAPROD	-8.738281	14.17001	-0.616674	0.5413
DIFLNBAPROD(-1)	-14.33536	14.35709	-0.998486	0.3247
DIFLNBAPROD(-2)	37.13132	14.28246	2.599786	0.0134
LNBER	-1.526896	2.415497	-0.632125	0.5313
LNBER(-1)	5.176339	3.374806	1.533818	0.1338
LNBER(-2)	-7.897351	3.419611	-2.309430	0.0268
LNBER(-3)	5.038665	2.382707	2.114681	0.0414
C	-0.755958	1.058810	-0.713970	0.4798

R-squared	0.394392	Mean dependent var	0.680000
Adjusted R-squared	0.259813	S.D. dependent var	0.844794
S.E. of regression	0.726811	Akaike info criterion	2.376557
Sum squared resid	19.01717	Schwarz criterion	2.737889
Log likelihood	-44.47253	Hannan-Quinn criter.	2.511258
F-statistic	2.930553	Durbin-Watson stat	1.845973
Prob(F-statistic)	0.012563		

*Note: p-values and any subsequent tests do not account for model selection.

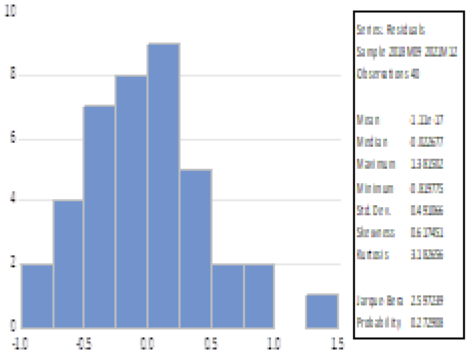
Table B - 19

Brazilian Model 3. Residual's diagnostics and coefficient stability

Date: 10/15/22 Time: 12:44
Sample (adjusted): 2018M09 2021M12
Q-statistic probabilities adjusted for 2 dynamic regressors

	AC	PAC	Q-Stat	Prob*
1	-0.038	-0.038	0.0636	0.801
2	-0.202	-0.204	1.8692	0.393
3	-0.000	-0.018	1.8692	0.600
4	-0.069	-0.116	2.0934	0.719
5	0.008	-0.005	2.0964	0.836
6	-0.172	-0.224	3.5565	0.736
7	-0.084	-0.118	3.9147	0.790
8	-0.044	-0.178	4.0165	0.856
9	0.377	0.352	11.710	0.230
10	0.078	0.028	12.054	0.281
11	-0.097	0.083	12.595	0.321
12	0.114	0.087	13.378	0.342
13	-0.137	-0.096	14.540	0.337
14	-0.052	-0.062	14.715	0.398
15	-0.065	-0.004	14.995	0.452
16	-0.092	-0.041	15.591	0.482
17	-0.107	-0.135	16.423	0.494
18	0.168	0.056	18.567	0.419
19	0.016	-0.175	18.587	0.484
20	-0.082	-0.066	19.156	0.512

*Probabilities may not be valid for this equation specification.



Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 8 lags

F-statistic	1.047845	Prob. F(8,13)	0.4511
Obs*R-squared	15.68134	Prob. Chi-Square(8)	0.0472

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 10/15/22 Time: 12:48
Sample: 2018M09 2021M12
Included observations: 40
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BF_BINF(-1)	0.073862	0.381337	0.193693	0.8494
BF_BINF(-2)	0.281858	0.358273	0.786712	0.4456
BENINF	0.040976	0.073347	0.558663	0.5859
BENINF(-1)	0.004313	0.065523	0.065831	0.9485
BENINF(-2)	-0.018659	0.061109	-0.305340	0.7649
BENINF(-3)	0.017525	0.072208	0.242705	0.8120
BENINF(-4)	0.014538	0.061716	0.235556	0.8174
BENINF(-5)	0.039954	0.063457	0.629617	0.5399
BENINF(-6)	0.001854	0.067950	0.027285	0.9786
BENINF(-7)	-0.012082	0.072190	-0.167366	0.8697
DIFLNBNEER	0.605302	4.038791	0.149872	0.8832
DIFLNBNEER(-1)	3.939875	4.303085	0.915593	0.3766
DIFLNBNEER(-2)	0.657994	4.806799	0.136888	0.8932
DIFLNBNEER(-3)	4.141238	4.299841	0.963114	0.3531
DIFLNBNEER(-4)	1.952983	3.979323	0.490783	0.6318
DIFLNBNEER(-5)	4.704948	4.316692	1.089943	0.2955
DIFLNBNEER(-6)	0.795647	3.924532	0.202737	0.8425
DIFLNBNEER(-7)	1.500571	4.006479	0.374536	0.7140
C	-0.487731	0.288333	-1.691556	0.1145
RESID(-1)	-0.320692	0.462652	-0.693161	0.5004
RESID(-2)	-0.933647	0.410099	-2.276637	0.0404
RESID(-3)	-0.394445	0.423320	-0.931790	0.3684
RESID(-4)	-0.515943	0.340609	-1.514763	0.1538
RESID(-5)	-0.206922	0.331831	-0.623576	0.5437
RESID(-6)	-0.670601	0.348944	-1.921802	0.0768
RESID(-7)	-0.177971	0.365177	-0.487354	0.6341
RESID(-8)	-0.602270	0.390445	-1.542522	0.1469

R-squared	0.392033	Mean dependent var	-1.11E-17
Adjusted R-squared	-0.823900	S.D. dependent var	0.491066
S.E. of regression	0.663193	Akaike info criterion	2.242569
Sum squared resid	5.717730	Schwarz criterion	3.382563
Log likelihood	-17.85139	Hannan-Quinn criter.	2.654755
F-statistic	0.322414	Durbin-Watson stat	1.760380
Prob(F-statistic)	0.993221		

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

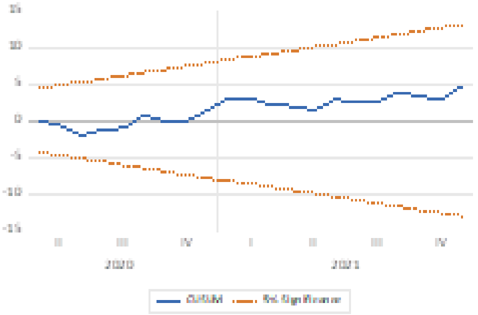
F-statistic	0.826414	Prob. F(18,21)	0.6559
Obs*R-squared	16.58566	Prob. Chi-Square(18)	0.5517
Scaled explained SS	4.988921	Prob. Chi-Square(18)	0.9989

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/15/22 Time: 12:50
Sample: 2018M09 2021M12
Included observations: 40

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.225675	0.114972	1.962864	0.0630
BF_BINF(-1)	0.127267	0.100348	1.268252	0.2186
BF_BINF(-2)	-0.168621	0.097705	-1.725816	0.0991
BENINF	-0.035078	0.032772	-1.070370	0.2966
BENINF(-1)	0.042144	0.031929	1.319922	0.2011
BENINF(-2)	-0.034749	0.030808	-1.127917	0.2721
BENINF(-3)	0.011806	0.030615	0.385625	0.7037
BENINF(-4)	0.024252	0.028531	0.850016	0.4049
BENINF(-5)	0.011801	0.028608	0.412508	0.6841
BENINF(-6)	-0.008082	0.031216	-0.258893	0.7982
BENINF(-7)	0.042296	0.032670	1.294642	0.2095
DIFLNBNEER	-0.227092	1.717426	-0.132228	0.8961
DIFLNBNEER(-1)	1.007188	1.876651	0.536694	0.5971
DIFLNBNEER(-2)	1.496978	1.904388	0.786068	0.4406
DIFLNBNEER(-3)	-2.764129	1.907678	-1.448949	0.1621
DIFLNBNEER(-4)	3.385746	1.855182	1.825021	0.0823
DIFLNBNEER(-5)	-1.653208	1.872818	-0.882738	0.3874
DIFLNBNEER(-6)	-0.648549	1.941507	-0.334044	0.7417
DIFLNBNEER(-7)	-1.138980	1.980232	-0.575175	0.5713

R-squared	0.414642	Mean dependent var	0.235117
Adjusted R-squared	-0.087094	S.D. dependent var	0.351783
S.E. of regression	0.366782	Akaike info criterion	1.137544
Sum squared resid	2.825108	Schwarz criterion	1.939762
Log likelihood	-3.750883	Hannan-Quinn criter.	1.427601
F-statistic	0.826414	Durbin-Watson stat	1.789237
Prob(F-statistic)	0.655907		

Brazilian Model 3. Residual's diagnostics and coefficient stability



Variance Inflation Factors
Date: 10/15/22 Time: 12:53
Sample: 2018M01 2021M12
Included observations: 40

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
BF_BINF(-1)	0.033522	3.537395	2.128389
BF_BINF(-2)	0.031779	3.354412	2.026431
BENINF	0.003575	1.954664	1.749517
BENINF(-1)	0.003394	1.854034	1.661243
BENINF(-2)	0.003160	1.815540	1.608024
BENINF(-3)	0.003120	2.097878	1.826533
BENINF(-4)	0.002710	1.657271	1.459149
BENINF(-5)	0.002724	1.657271	1.465711
BENINF(-6)	0.003244	1.628952	1.476138
BENINF(-7)	0.003553	1.754401	1.607983
DIFLNBNEER	9.818950	1.258203	1.226862
DIFLNBNEER(-1)	11.72400	1.499506	1.463812
DIFLNBNEER(-2)	12.07313	1.544030	1.506681
DIFLNBNEER(-3)	12.11488	1.506115	1.476956
DIFLNBNEER(-4)	11.45729	1.447976	1.412668
DIFLNBNEER(-5)	11.67616	1.507513	1.463939
DIFLNBNEER(-6)	12.54835	1.617740	1.572240
DIFLNBNEER(-7)	13.05392	1.604955	1.528913
C	0.044004	3.930346	NA

Table B - 20

Brazilian model 3 . Long-run test for cointegration.

ARDL Long Run Form and Bounds Test
Dependent Variable: D(BF_BINF)
Selected Model: ARDL(2, 7, 7)
Case 3: Unrestricted Constant and No Trend
Date: 10/15/22 Time: 12:53
Sample: 2018M01 2021M12
Included observations: 40

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.272963	0.209772	1.301236	0.2073
BF_BINF(-1)*	-0.619587	0.160495	-3.860465	0.0009
BENINF(-1)	0.104700	0.143653	0.728834	0.4742
DIFLNBNEER(-1)	15.51229	10.11939	1.532927	0.1402
D(BF_BINF(-1))	0.294508	0.178268	1.652059	0.1134
D(BENINF)	-0.050306	0.059794	-0.841308	0.4097
D(BENINF(-1))	-0.005503	0.108298	-0.050810	0.9600
D(BENINF(-2))	-0.097877	0.101932	-0.960224	0.3479
D(BENINF(-3))	-0.078469	0.098407	-0.797400	0.4341
D(BENINF(-4))	-0.068896	0.094493	-0.729112	0.4740
D(BENINF(-5))	-0.061661	0.085155	-0.724101	0.4770
D(BENINF(-6))	-0.122911	0.059607	-2.062009	0.0518
D(DIFLNBNEER)	-0.717952	3.133520	-0.229120	0.8210
D(DIFLNBNEER(-1))	-12.64218	8.425811	-1.500411	0.1484
D(DIFLNBNEER(-2))	-13.95257	7.145816	-1.952551	0.0643
D(DIFLNBNEER(-3))	-14.70873	6.108490	-2.407916	0.0253
D(DIFLNBNEER(-4))	-8.564389	5.307874	-1.613525	0.1216
D(DIFLNBNEER(-5))	-12.62789	4.268194	-2.958603	0.0075
D(DIFLNBNEER(-6))	-8.946673	3.613021	-2.476231	0.0219

* p-value incompatible with t-Bounds distribution.

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BENINF	0.168983	0.231507	0.729924	0.4735
DIFLNBNEER	25.03650	16.61201	1.507133	0.1467

EC = BF_BINF - (0.1690*BENINF + 25.0365*DIFLNBNEER)

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BENINF	0.168983	0.231507	0.729924	0.4735
DIFLNBNEER	25.03650	16.61201	1.507133	0.1467

EC = BF_BINF - (0.1690*BENINF + 25.0365*DIFLNBNEER)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	5.294701	10%	3.17	4.14
k	2	5%	3.79	4.85
		2.5%	4.41	5.52
		1%	5.15	6.36
Actual Sample Size	40		Finite Sample: n=40	
		10%	3.373	4.377
		5%	4.133	5.26
		1%	5.893	7.337

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-3.860465	10%	-2.57	-3.21
		5%	-2.86	-3.53
		2.5%	-3.13	-3.8
		1%	-3.43	-4.1

Table B - 21

Thailand ADF Unit Roots test

At level

		COI	COP	GFI	LNCOI	LNCOP	LNGFI	LNTAPI
With Constant	t-Statistic	-1.4284	-1.4097	0.7051	-1.5773	-1.5895	0.4999	-2.2123
	Prob.	***0.5601***	***0.5693***	***0.9911***	***0.4857***	***0.4796***	***0.9850***	***0.2048***
		n0	n0	n0	n0	n0	n0	n0
With Constant & Trend	t-Statistic	-1.2342	-1.1990	-1.0597	-1.4147	-1.4200	-1.1852	-3.2727
	Prob.	***0.8910***	***0.8987***	***0.9250***	***0.8431***	***0.8414***	***0.9020***	***0.0836***
		n0	n0	n0	n0	n0	n0	*
Without Constant & Trend	t-Statistic	-0.0472	-0.0994	1.5187	0.0962	0.0365	1.3204	0.4414
	Prob.	***0.6617***	***0.6440***	***0.9665***	***0.7082***	***0.6893***	***0.9509***	***0.8055***
		n0	n0	n0	n0	n0	n0	n0

At First Difference

		d(COI)	d(COP)	d(GFI)	d(LNCOI)	d(LNCOP)	d(LNGFI)	d(LNTAPI)
With Constant	t-Statistic	-5.6372	-5.6456	-5.4011	-5.9931	-5.9613	-5.4387	-4.8529
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0002***
		***	***	***	***	***	***	***
With Constant & Trend	t-Statistic	-5.6562	-5.6888	-5.8962	-5.9960	-5.9767	-5.8676	-4.7817
	Prob.	***0.0001***	***0.0001***	***0.0001***	***0.0001***	***0.0001***	***0.0001***	***0.0019***
		***	***	***	***	***	***	***
Without Constant & Trend	t-Statistic	-5.6990	-5.7114	-5.2557	-6.0607	-6.0306	-5.3288	-4.8752
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***	***	***

At Level

		LNTAPI	LNTAPROD	LNTEXP	LNTFIMP	LNTIR	LNTLEI	LNTNEER	TAPI
With Constant	t-Statistic	-2.2123	-5.5614	-3.5833	-1.7179	-0.3136	-0.0947	-1.4699	-2.1985
	Prob.	***0.2048***	***0.0000***	***0.0099***	***0.4156***	***0.9149***	***0.9438***	***0.5398***	***0.2096***
		n0	***	***	n0	n0	n0	n0	n0
With Constant & Trend	t-Statistic	-3.2727	-5.8534	-3.6441	-5.7970	-1.4248	-3.2210	-1.1256	-4.2421
	Prob.	***0.0836***	***0.0001***	***0.0369***	***0.0001***	***0.8406***	***0.0928***	***0.9134***	***0.0085***
		*	***	**	***	n0	*	n0	***
Without Constant & Trend	t-Statistic	0.4414	0.0382	0.2086	0.3504	-0.0905	1.6820	-0.1093	0.3389
	Prob.	***0.8055***	***0.6899***	***0.7425***	***0.7819***	***0.6473***	***0.9759***	***0.6407***	***0.7789***
		n0	n0	n0	n0	n0	n0	n0	n0

At First Difference

		d(LNTAPI)	d(LNTAP...	d(LNTEXP)	d(LNTFIMP)	d(LNTIR)	d(LNTLEI)	d(LNTNE...	d(TAPI)
With Constant	t-Statistic	-4.8529	-9.1970	-7.8982	-9.1759	-3.0798	-9.7625	-4.6176	-4.9149
	Prob.	***0.0002***	***0.0000***	***0.0000***	***0.0000***	***0.0353***	***0.0000***	***0.0005***	***0.0002***
		***	***	***	***	**	***	***	***
With Constant & Trend	t-Statistic	-4.7817	-9.1084	-7.8053	-9.0631	-3.0343	-9.7579	-4.9637	-4.8433
	Prob.	***0.0019***	***0.0000***	***0.0000***	***0.0000***	***0.1346***	***0.0000***	***0.0011***	***0.0016***
		***	***	***	***	n0	***	***	***
Without Constant & Trend	t-Statistic	-4.8752	-9.3013	-7.9656	-9.2629	-2.8817	-9.4270	-4.6731	-4.9388
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0049***	***0.0000***	***0.0000***	***0.0000***
		***	***	***	***	***	***	***	***

At Level

Thailand ADF Unit Roots test

		TAPROD	TEINF	TF_BINF	TFEXP	TFIMP	TIR	TLEI	TNEER
With Constant	t-Statistic	-5.2971	-6.2489	-5.3912	-3.5354	-1.7151	-0.3595	-0.0667	-1.4885
	Prob.	***0.0001***	***0.0000***	***0.0000***	***0.0112***	***0.4170***	***0.9075***	***0.9469***	***0.5305***
		***	***	***	**	n0	n0	n0	n0
With Constant & Trend	t-Statistic	-6.5012	-6.3222	-5.3468	-3.6527	-5.4596	-1.4120	-3.1934	-1.1528
	Prob.	***0.0000***	***0.0000***	***0.0003***	***0.0361***	***0.0002***	***0.8445***	***0.0982***	***0.9083***
		***	***	***	**	***	n0	*	n0
Without Constant & Trend	t-Statistic	-0.6766	-6.2997	-5.1552	-0.0368	0.1751	-1.6555	1.6912	-0.1448
	Prob.	***0.4185***	***0.0000***	***0.0000***	***0.6654***	***0.7323***	***0.0919***	***0.9764***	***0.6283***
		n0	***	***	n0	n0	*	n0	n0

At First Difference

		d(TAPROD)	d(TEINF)	d(TF_BINF)	d(TFEXP)	d(TFIMP)	d(TIR)	d(TLEI)	d(TNEER)
With Constant	t-Statistic	-10.1532	-6.9281	-8.7445	-7.8078	-9.1975	-5.9073	-9.7498	-4.5750
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0006***
		***	***	***	***	***	***	***	***
With Constant & Trend	t-Statistic	-10.0448	-6.8410	-8.6524	-7.7163	-9.0833	-5.8488	-9.7526	-4.9082
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0001***	***0.0000***	***0.0013***
		***	***	***	***	***	***	***	***
Without Constant & Trend	t-Statistic	-10.2665	-7.0273	-8.8411	-7.8750	-9.2874	-3.0574	-9.4091	-4.6298
	Prob.	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0000***	***0.0030***	***0.0000***	***0.0000***
		***	***	***	***	***	***	***	***

Table B - 22

THAILAND MATRIX OF CORRELATION

	GFI	LNCOI	LNCOP	LNGFI	LNTAPI	LNTAPROD	LNTEXP
COI	0.27352856...	0.98567366...	0.98148172...	0.27812013...	-0.2413639...	-0.0183169...	0.07199019
COP	0.32883897...	0.98308884...	0.98454393...	0.33465461...	-0.1958365...	-0.0284292...	0.08168787
DIFCOI	0.31144848...	0.28036215...	0.29911585...	0.32383460...	0.10257055...	-0.1030805...	0.00056487
DIFCOP	0.31402320...	0.25645580...	0.27647248...	0.32638174...	0.11772160...	-0.0927766...	-0.0130685.
DIFLNCOI	0.24260971...	0.27823504...	0.29187122...	0.25497285...	0.03665514...	-0.0314995...	-0.0497864.
DIFGFI	0.41107170...	-0.0060663...	0.01691328...	0.42228632...	0.36052114...	0.11794475...	-0.0350446.
DIFLNCOP	0.23866583...	0.26027215...	0.27451289...	0.25097489...	0.04192499...	-0.0234516...	-0.0616343.
DIFLNTAPI	-0.1818977...	0.03323365...	0.03861295...	-0.1582503...	0.19913222...	0.13584091...	-0.5574100.
DIFLNGFI	0.38073404...	-0.0054321...	0.01651300...	0.39381072...	0.33058767...	0.13249409...	-0.0661918.
DIFLNTEXP	0.05874593...	-0.1284469...	-0.1229060...	0.05153025...	0.20181239...	-0.0826617...	0.51183756
DIFLNTAPROD	-0.0996150...	-0.0179672...	-0.0243770...	-0.1075012...	-0.1618062...	0.52490034...	0.13558283
DIFLNTFIMP	0.01414829...	-0.0685622...	-0.0639967...	0.01180982...	0.04740806...	0.08063320...	0.30127257
DIFLNTIR	0.19963843...	0.37302398...	0.39209325...	0.20809763...	-0.0010486...	0.16646671...	-0.1955165.
DIFLNTLEI	0.56756808...	-0.3965750...	-0.3792255...	0.55772696...	0.78359357...	-0.0922904...	0.16989599
DIFLNTNEER	-0.3998465...	0.00102973...	-0.0090305...	-0.3960223...	-0.3894146...	0.17834828...	-0.0955026.
DIFTAPI	-0.1915857...	0.02780241...	0.03293012...	-0.1677018...	0.20146510...	0.13735411...	-0.5581565.
DIFTAPROD	-0.0783679...	-0.0196759...	-0.0250881...	-0.0849088...	-0.1228226...	0.49576836...	0.12732039
DIFTEINF	-0.0204052...	0.01642921...	0.01176361...	-0.0103887...	-0.0599917...	-0.0278516...	0.01237319
DIFTF_BINF	-0.0400771...	0.06257049...	0.06176218...	-0.0365407...	-0.0292752...	-0.0464149...	0.00096092
DIFTFEXP	0.06168790...	-0.1297976...	-0.1241695...	0.05424295...	0.20242274...	-0.0803477...	0.51240340
DIFTFIMP	0.02161323...	-0.0698909...	-0.0649028...	0.01872046...	0.05768799...	0.07523780...	0.28711573
DIFTILEI	-0.1856919...	-0.1624046...	-0.1636649...	-0.1889340...	0.07336853...	0.09398573...	-0.1262314.
DIFTIR	0.17785750...	0.25327471...	0.27270627...	0.18511264...	-0.0203058...	0.15047130...	-0.1473010.
DIFTNEER	-0.3967829...	0.00121872...	-0.0089188...	-0.3931211...	-0.3905156...	0.17655470...	-0.0903446.
GFI	1	0.28611165...	0.32891486...	0.99889438...	0.68938817...	-0.1695663...	0.33586322
LNCOI	0.28611165...	1	0.99767970...	0.29360984...	-0.2030882...	0.03846045...	-0.0140445.
LNCOP	0.32891486...	0.99767970...	1	0.33762766...	-0.1644267...	0.03581238...	-0.0120168.
LNGFI	0.99889438...	0.29360984...	0.33762766...	1	0.69655783...	-0.1573381...	0.30487285
LNTAPI	0.68938817...	-0.2030882...	-0.1644267...	0.69655783...	1	-0.2057691...	0.08540783
LNTAPROD	-0.1695663...	0.03846045...	0.03581238...	-0.1573381...	-0.2057691...	1	-0.3434023.
LNTEXP	0.33586322...	-0.0140445...	-0.0120168...	0.30487285...	0.08540783...	-0.3434023...	1
LNTFIMP	0.68757748...	0.00068827...	0.02811414...	0.67696631...	0.53952771...	-0.1502156...	0.51260981
LNTIR	-0.5281883...	0.52100206...	0.48620680...	-0.5249678...	-0.7531005...	0.12748904...	-0.1480217.
LNTLEI	0.62885627...	-0.3534071...	-0.3153395...	0.62583100...	0.82410164...	0.00663708...	0.13389933
LNTNEER	-0.1574958...	-0.3619887...	-0.3863190...	-0.1582211...	0.25209147...	0.17739364...	-0.2541647.
TAPI	0.69424734...	-0.1923335...	-0.1536488...	0.70131981...	0.99946435...	-0.2003437...	0.08964592
TAPROD	-0.1413712...	0.00340978...	0.00073736...	-0.1315909...	-0.1705356...	0.98242064...	-0.2684478.
TEINF	0.12743679...	0.29042331...	0.29456123...	0.14146386...	0.03498557...	-0.0524048...	-0.1845405.
TF_BINF	-0.1996695...	0.12647046...	0.10957518...	-0.2073948...	-0.1691436...	-0.2463207...	0.10773950
TFEXP	0.35860500...	-0.0201120...	-0.0175361...	0.32718838...	0.10480720...	-0.3488453...	0.99849391
TFIMP	0.70599381...	0.02774503...	0.05488886...	0.69341458...	0.53275616...	-0.1633580...	0.53007796
TIR	-0.5071156...	0.53628347...	0.50333053...	-0.5039290...	-0.7390896...	0.11008309...	-0.1348149.
TLEI	0.63169896...	-0.3492238...	-0.3110093...	0.62878550...	0.82600417...	0.00560337...	0.13485473
TNEER	-0.1600227...	-0.3563940...	-0.3809360...	-0.1606014...	0.24549516...	0.18044494...	-0.2574613.

	LNTFIMP	LNTIR	LNTLEI	LNTNEER	TAPI	TAPROD	TEINF
COI	-0.0004377...	0.54638845...	-0.4067768...	-0.4286488...	-0.2307154...	-0.0446857...	0.21655714..
COP	0.03571246...	0.50520949...	-0.3632051...	-0.4634323...	-0.1851232...	-0.0541934...	0.21876574..
DIFCOI	0.18844015...	-0.1938839...	0.14463301...	0.06784265...	0.10439549...	-0.1162371...	0.59074816..
DIFCOP	0.20187376...	-0.2146505...	0.16806947...	0.08943332...	0.11925579...	-0.1077939...	0.58698041..
DIFLNCOI	0.13426367...	-0.1837908...	0.12717733...	0.08584603...	0.03959115...	-0.0412678...	0.69486857..
DIFGFI	0.33246483...	-0.3490301...	0.37662857...	0.23864216...	0.36419011...	0.09894074...	0.28221215..
DIFLNCOP	0.13909106...	-0.1972181...	0.14080733...	0.10026817...	0.04458365...	-0.0341350...	0.69754726..
DIFLNTAPI	-0.0986980...	0.05735347...	0.01880291...	0.23661411...	0.19954796...	0.07007363...	0.15145939..
DIFLNGFI	0.30367788...	-0.3365402...	0.35615817...	0.25199766...	0.33358645...	0.11097698...	0.31385760..
DIFLNTEXP	0.22337645...	-0.0407785...	0.06191118...	-0.0947422...	0.20575126...	-0.0803705...	-0.3345059...
DIFLNTAPROD	-0.0588973...	-0.0255174...	0.03804371...	0.01278502...	-0.1616624...	0.62035987...	-0.0115277...
DIFLNTFIMP	0.55962711...	-0.0246184...	0.03217566...	0.03607673...	0.05246522...	0.06069703...	-0.1048508...
DIFLNTIR	0.04392869...	0.15983820...	0.01721687...	-0.2874927...	0.00449884...	0.15148373...	0.04841842..
DIFLNTLEI	0.51515189...	-0.8814959...	0.88726231...	0.51534375...	0.78014395...	-0.0505054...	0.06310708..
DIFLNTNEER	-0.0925462...	0.33830152...	-0.3014413...	0.12899710...	-0.3861632...	0.15711144...	0.10097238..
DIFTAPI	-0.1055341...	0.05379923...	0.02503187...	0.23928260...	0.20270502...	0.07189556...	0.13924159..
DIFTAPROD	-0.0468576...	-0.0223376...	0.03423767...	0.00383814...	-0.1227563...	0.60082293...	-0.0163331...
DIFTEINF	-0.0618647...	-0.0537773...	-0.0085042...	0.07682665...	-0.0547597...	-0.0248051...	0.65532209..
DIFTF_BINF	0.14912508...	0.03733953...	-0.0473661...	0.01189576...	-0.0225030...	-0.0679769...	0.25460244..
DIFTFEXP	0.23442359...	-0.0364976...	0.05741731...	-0.0910134...	0.20651874...	-0.0797608...	-0.3475980...
DIFTFIMP	0.55280248...	-0.0227493...	0.03400823...	0.03851583...	0.06288972...	0.05631258...	-0.1213361...
DIFTILEI	-0.0286895...	-0.0868179...	0.20525268...	0.07738677...	0.07878168...	0.11885956...	-0.0536859...
DIFTIR	0.05822122...	0.10233398...	0.01749647...	-0.3487398...	-0.0140696...	0.14144933...	0.04834671..
DIFTNEER	-0.0962713...	0.33625044...	-0.2978192...	0.13103585...	-0.3874111...	0.15741765...	0.10381093..
GFI	0.68757748...	-0.5281883...	0.62885627...	-0.1574958...	0.69424734...	-0.1413712...	0.12743679..
LNCOI	0.00068827...	0.52100206...	-0.3534071...	-0.3619887...	-0.1923335...	0.00340978...	0.29042331..
LNCOP	0.02811414...	0.48620680...	-0.3153395...	-0.3863190...	-0.1536488...	0.00073736...	0.29456123..
LNGFI	0.67696631...	-0.5249678...	0.62583100...	-0.1582211...	0.70131981...	-0.1315909...	0.14146386..
LNTAPI	0.53952771...	-0.7531005...	0.82410164...	0.25209147...	0.99946435...	-0.1705356...	0.03498557..
LNTAPROD	-0.1502156...	0.12748904...	0.00663708...	0.17739364...	-0.2003437...	0.98242064...	-0.0524048...
LNTEXP	0.51260981...	-0.1480217...	0.13389933...	-0.2541647...	0.08964592...	-0.2684478...	-0.1845405...
LNTFIMP	1	-0.4650705...	0.52532241...	0.02197485...	0.54252945...	-0.1192793...	-0.0398774...
LNTIR	-0.4650705...	1	-0.9025616...	-0.2649793...	-0.7494194...	0.07613998...	-0.1337013...
LNTLEI	0.52532241...	-0.9025616...	1	0.29376678...	0.82704187...	0.04544476...	0.08705060..
LNTNEER	0.02197485...	-0.2649793...	0.29376678...	1	0.24592648...	0.16313098...	0.07134341..
TAPI	0.54252945...	-0.7494194...	0.82704187...	0.24592648...	1	-0.1660191...	0.03689539..
TAPROD	-0.1192793...	0.07613998...	0.04544476...	0.16313098...	-0.1660191...	1	-0.0473233...
TEINF	-0.0398774...	-0.1337013...	0.08705060...	0.07134341...	0.03689539...	-0.0473233...	1
TF_BINF	0.08398993...	0.19334022...	-0.2555252...	-0.0953731...	-0.1720397...	-0.2197573...	0.24054564..
TFEXP	0.53553370...	-0.1666746...	0.14796734...	-0.2446138...	0.10874322...	-0.2746707...	-0.1894435...
TFIMP	0.99420329...	-0.4500756...	0.51649492...	-0.0001024...	0.53604978...	-0.1317084...	-0.0534491...
TIR	-0.4462579...	0.99319779...	-0.8792862...	-0.2840568...	-0.7348885...	0.06000221...	-0.0965091...
TLEI	0.52662263...	-0.9019003...	0.99996995...	0.29075752...	0.82906817...	0.04433085...	0.08815176..
TNEER	0.01634243...	-0.2592416...	0.28764340...	0.99987718...	0.23932845...	0.16589658...	0.07247309..

	TF_BINF	TFEXP	TFIMP	TIR	TLEI	TNEER
COI	0.147913	0.065246	0.027008	0.556046	-0.402374	-0.423029
COP	0.127905	0.075741	0.063056	0.516685	-0.358629	-0.458047
DIFCOI	0.026156	0.004803	0.189729	-0.147946	0.147244	0.068829
DIFCOP	0.015037	-0.007804	0.203706	-0.168120	0.170515	0.090193
DIFLNCOI	0.030202	-0.044766	0.134713	-0.133752	0.129095	0.087128
DIFGFI	-0.228334	-0.023704	0.331425	-0.316932	0.377401	0.236499
DIFLNCOP	0.025385	-0.056082	0.139793	-0.146655	0.142584	0.101426
DIFLNTAPI	-0.012325	-0.557364	-0.109040	0.061644	0.019885	0.235356
DIFLNGFI	-0.225405	-0.056306	0.298593	-0.303201	0.356860	0.250064
DIFLNTEXP	-0.001742	0.502034	0.221472	-0.052756	0.063278	-0.098284
DIFLNTAPROD	0.019254	0.126679	-0.058478	-0.035942	0.036536	0.014739
DIFLNTFIMP	0.092257	0.299621	0.536776	-0.024857	0.032615	0.034759
DIFLNTIR	0.035553	-0.201052	0.052416	0.203063	0.019733	-0.287361
DIFLNTLEI	-0.170603	0.191727	0.506221	-0.869392	0.886400	0.509158
DIFLNTNEER	0.000483	-0.104042	-0.100750	0.370271	-0.301970	0.129334
DIFTAPI	-0.025454	-0.558836	-0.116762	0.057577	0.026264	0.238104
DIFTAPROD	0.056172	0.118632	-0.047624	-0.033686	0.032872	0.005208
DIFTEINF	0.106765	0.006529	-0.088610	-0.030544	-0.008045	0.077308
DIFTF_BINF	0.642608	-3.44E-05	0.110555	0.033520	-0.046337	0.011026
DIFTFEXP	-0.000989	0.504391	0.234638	-0.048843	0.058833	-0.094515
DIFTFIMP	0.061165	0.288164	0.539624	-0.022849	0.034442	0.037257
DIFTILEI	-0.076474	-0.130355	-0.027566	-0.097822	0.204437	0.076499
DIFTIR	0.010472	-0.150904	0.064454	0.155756	0.019746	-0.350056
DIFTNEER	-0.008133	-0.099292	-0.103983	0.368898	-0.298390	0.131486
GFI	-0.199670	0.358605	0.705994	-0.507116	0.631699	-0.160023
LNCOI	0.126470	-0.020112	0.027745	0.536283	-0.349224	-0.356394
LNCOP	0.109575	-0.017536	0.054889	0.503331	-0.311009	-0.380936
LNGFI	-0.207395	0.327188	0.693415	-0.503929	0.628786	-0.160601
LNTAPI	-0.169144	0.104807	0.532756	-0.739090	0.826004	0.245495
LNTAPROD	-0.246321	-0.348845	-0.163358	0.110083	0.005603	0.180445
LNTEXP	0.107740	0.998494	0.530078	-0.134815	0.134855	-0.257461
LNTFIMP	0.083990	0.535534	0.994203	-0.446258	0.526623	0.016342
LNTIR	0.193340	-0.166675	-0.450076	0.993198	-0.901900	-0.259242
LNTLEI	-0.255525	0.147967	0.516495	-0.879286	0.999970	0.287643
LNTNEER	-0.095373	-0.244614	-0.000102	-0.284057	0.290758	0.999877
TAPI	-0.172040	0.108743	0.536050	-0.734889	0.829068	0.239328
TAPROD	-0.219757	-0.274671	-0.131708	0.060002	0.044331	0.165897
TEINF	0.240546	-0.189444	-0.053449	-0.096509	0.088152	0.072473
TF_BINF	1.000000	0.104159	0.060215	0.206626	-0.255405	-0.099763
TFEXP	0.104159	1.000000	0.555402	-0.154601	0.148904	-0.248042
TFIMP	0.060215	0.555402	1.000000	-0.430534	0.517884	-0.005588
TIR	0.206626	-0.154601	-0.430534	1.000000	-0.878448	-0.279293
TLEI	-0.255405	0.148904	0.517884	-0.878448	1.000000	0.284630
TNEER	-0.099763	-0.248042	-0.005588	-0.279293	0.284630	1.000000

Table B - 23

Thailand. Model 1 . Cointegration Bound test

ARDL Long Run Form and Bounds Test

Dependent Variable: D(TF_BINF)

Selected Model: ARDL(1, 4, 3, 0)

Case 3: Unrestricted Constant and No Trend

Date: 10/19/22 Time: 14:33

Sample: 2018M01 2021M12

Included observations: 38

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	165.8241	120.7410	1.373387	0.1814
TF_BINF(-1)*	-0.831868	0.164716	-5.050306	0.0000
DIFLNTAPROD(-1)	-1.210917	0.545638	-2.219267	0.0354
DIFTENINF(-1)	0.079003	0.030320	2.605619	0.0150
DIFLNTLEI**	-0.000225	0.000164	-1.372939	0.1815
D(DIFLNTAPROD)	-0.067020	0.187473	-0.357489	0.7236
D(DIFLNTAPROD(-1))	0.792796	0.412204	1.923308	0.0655
D(DIFLNTAPROD(-2))	0.744943	0.308581	2.414097	0.0231
D(DIFLNTAPROD(-3))	0.531583	0.187853	2.829778	0.0089
D(DIFTENINF)	0.022530	0.010126	2.225035	0.0350
D(DIFTENINF(-1))	-0.046585	0.017039	-2.734066	0.0111
D(DIFTENINF(-2))	-0.018163	0.011115	-1.634060	0.1143

* p-value incompatible with t-Bounds distribution.

** Variable interpreted as Z = Z(-1) + D(Z).

Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFLNTAPROD	-1.455660	0.680896	-2.137861	0.0421
DIFTENINF	0.094970	0.040499	2.344997	0.0269
DIFLNTLEI	-0.000270	0.000191	-1.417389	0.1682

EC = TF_BINF - (-1.4557*DIFLNTAPROD + 0.0950*DIFTENINF -0.0003 *DIFLNTLEI)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	8.599887	10%	2.72	3.7
k	3	5%	3.23	4.3
		2.5%	3.69	4.8
		1%	4.29	5.6
			Finite Sample: n=40	
Actual Sample Size	38			
		10%	2.933	4.0
		5%	3.548	4.8
		1%	5.018	6.6
			Finite Sample: n=35	
		10%	2.958	4.1
		5%	3.615	4.9
		1%	5.198	6.8

t-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-5.050306	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

Table B - 24

Thailand Model 1. Residual's diagnostics and stability

Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	0.420172	Prob. F(11,26)	0.9334
Obs*R-squared	5.735504	Prob. Chi-Square(11)	0.8904
Scaled explained SS	2.636338	Prob. Chi-Square(11)	0.9947

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/18/22 Time: 22:40
Sample: 2018M06 2021M07
Included observations: 38

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	50.41648	41.70081	1.209005	0.2375
TF_BINF(-1)	-0.005701	0.056889	-0.100211	0.9209
DIFLNTAPROD	-0.015755	0.064748	-0.243331	0.8097
DIFLNTAPROD(-1)	-0.113427	0.067403	-1.682818	0.1044
DIFLNTAPROD(-2)	-0.037124	0.070065	-0.529844	0.6007
DIFLNTAPROD(-3)	0.001717	0.067646	0.025384	0.9799
DIFLNTAPROD(-4)	-0.011226	0.064880	-0.173025	0.8640
DIFLNTLEI	-6.83E-05	5.65E-05	-1.207317	0.2382
DIFTENINF	-1.88E-05	0.003497	-0.005372	0.9958
DIFTENINF(-1)	-0.001094	0.003662	-0.298688	0.7676
DIFTENINF(-2)	0.000141	0.003507	0.040148	0.9683
DIFTENINF(-3)	-0.001428	0.003839	-0.371891	0.7130

R-squared	0.150934	Mean dependent var	0.071542
Adjusted R-squared	-0.208286	S.D. dependent var	0.101599
S.E. of regression	0.111680	Akaike info criterion	-1.294275
Sum squared resid	0.324281	Schwarz criterion	-0.777142
Log likelihood	36.59122	Hannan-Quinn criter.	-1.110283
F-statistic	0.420172	Durbin-Watson stat	2.023652
Prob(F-statistic)	0.933373		

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 4 lags

F-statistic	0.316930	Prob. F(4,22)	0.8636
Obs*R-squared	2.070397	Prob. Chi-Square(4)	0.7228

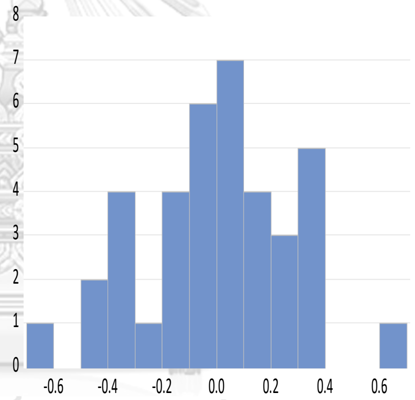
Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 10/18/22 Time: 22:39
Sample: 2018M06 2021M07
Included observations: 38
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TF_BINF(-1)	-0.125807	0.298255	-0.421811	0.6773
DIFLNTAPROD	-0.007914	0.206372	-0.038346	0.9698
DIFLNTAPROD(-1)	-0.021596	0.207482	-0.104085	0.9180
DIFLNTAPROD(-2)	-0.061233	0.234205	-0.261448	0.7962
DIFLNTAPROD(-3)	-0.009704	0.207567	-0.046753	0.9631
DIFLNTAPROD(-4)	-0.011536	0.199048	-0.057956	0.9543
DIFLNTLEI	-2.49E-05	0.000186	-0.133718	0.8948
DIFTENINF	-7.73E-05	0.011010	-0.007025	0.9945
DIFTENINF(-1)	0.000216	0.012692	0.016983	0.9866
DIFTENINF(-2)	-0.001530	0.011152	-0.137204	0.8921
DIFTENINF(-3)	0.000628	0.013495	0.046520	0.9633
C	18.35374	137.1709	0.133802	0.8948
RESID(-1)	0.175022	0.362990	0.482168	0.6344
RESID(-2)	-0.080188	0.221167	-0.362569	0.7204
RESID(-3)	-0.163935	0.224503	-0.730211	0.4730
RESID(-4)	-0.088356	0.235917	-0.374521	0.7116

R-squared	0.054484	Mean dependent var	5.24E-14
Adjusted R-squared	-0.590186	S.D. dependent var	0.271063
S.E. of regression	0.341817	Akaike info criterion	0.986481
Sum squared resid	2.570459	Schwarz criterion	1.675991
Log likelihood	-2.743138	Hannan-Quinn criter.	1.231803
F-statistic	0.084515	Durbin-Watson stat	1.930797
Prob(F-statistic)	0.999994		

Date: 10/18/22 Time: 22:38
Sample (adjusted): 2018M06 2021M07
Q-statistic probabilities adjusted for 1 dynamic regressor

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.073	0.073	0.2218	0.638
		2	-0.087	-0.093	0.5422	0.763
		3	-0.168	-0.156	1.7660	0.622
		4	-0.081	-0.068	2.0563	0.725
		5	-0.160	-0.187	3.2411	0.663
		6	0.036	0.015	3.3025	0.770
		7	-0.047	-0.116	3.4125	0.844
		8	0.059	0.010	3.5861	0.892
		9	0.163	0.137	4.9871	0.835
		10	-0.176	-0.264	6.6620	0.757
		11	-0.186	-0.135	8.6173	0.657
		12	-0.141	-0.174	9.7814	0.635
		13	0.119	0.065	10.649	0.640
		14	0.118	0.053	11.531	0.644
		15	0.013	-0.163	11.543	0.713
		16	0.067	0.107	11.850	0.754



Series: Residuals
Sample 2018M06 2021M07
Observations 38

Mean	5.24e-14
Median	0.012580
Maximum	0.666467
Minimum	-0.608298
Std. Dev.	0.271063
Skewness	-0.077232
Kurtosis	2.963722
Jarque-Bera	0.039861
Probability	0.980267

Variance Inflation Factors
Date: 10/18/22 Time: 22:41
Sample: 2018M01 2021M12
Included observations: 38

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
TF_BINF(-1)	0.027131	1.488095	1.386880
DIFLNTAPROD	0.035146	1.143569	1.143568
DIFLNTAPROD(-1)	0.038087	1.241874	1.241602
DIFLNTAPROD(-2)	0.041155	1.356923	1.355755
DIFLNTAPROD(-3)	0.038363	1.264898	1.263826
DIFLNTAPROD(-4)	0.035289	1.161451	1.160748
DIFLNTLEI	2.68E-08	5297872.	1.085995
DIFTENINF	0.000103	1.576091	1.575835
DIFTENINF(-1)	0.000112	1.730977	1.730872
DIFTENINF(-2)	0.000103	1.525124	1.524236
DIFTENINF(-3)	0.000124	1.576004	1.572490
C	14578.39	5298152.	NA

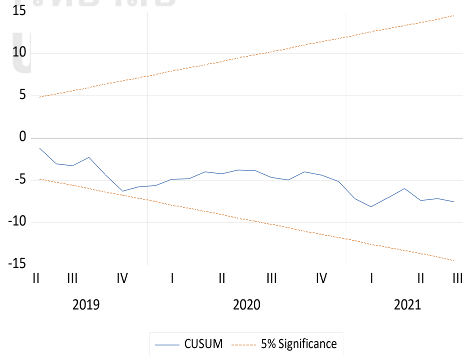


Table B - 25

Thailand. Model 2. Residual's diagnostic and Stability

Date: 10/19/22 Time: 14:17
Sample (adjusted): 2018M06 2021M12
Q-statistic probabilities adjusted for 2 dynamic regressors

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob*
		1	0.056	0.056	0.1451	0.703
		2	-0.090	-0.093	0.5265	0.769
		3	-0.077	-0.067	0.8156	0.846
		4	0.078	0.079	1.1145	0.892
		5	-0.050	-0.073	1.2400	0.941
		6	-0.014	0.002	1.2498	0.974
		7	-0.063	-0.063	1.4649	0.984
		8	0.073	0.067	1.7628	0.987
		9	-0.095	-0.111	2.2785	0.986
		10	-0.211	-0.206	4.8986	0.898
		11	-0.156	-0.141	6.3792	0.847
		12	0.113	0.062	7.1772	0.846
		13	-0.133	-0.199	8.3240	0.822
		14	0.098	0.133	8.9644	0.833
		15	-0.020	-0.059	8.9909	0.878
		16	0.037	-0.009	9.0914	0.910
		17	0.140	0.190	10.556	0.879
		18	-0.004	-0.085	10.557	0.912
		19	-0.179	-0.164	13.153	0.831
		20	-0.122	-0.223	14.396	0.810

*Probabilities may not be valid for this equation specification.

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 4 lags

F-statistic	0.560984	Prob. F(4,26)	0.6930
Obs*R-squared	3.416283	Prob. Chi-Square(4)	0.4907

Test Equation:
Dependent Variable: RESID
Method: ARDL
Date: 10/19/22 Time: 14:20
Sample: 2018M06 2021M12
Included observations: 43
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
TF_BINF(-1)	-0.304074	0.366610	-0.829421	0.4144
TF_BINF(-2)	0.345041	0.300011	1.150092	0.2606
DIFLNTAPI	0.068027	2.622968	0.025935	0.9795
DIFLNTAPI(-1)	-0.303184	2.578334	-0.117589	0.9073
DIFTENINF	-0.002431	0.011905	-0.204173	0.8398
DIFTENINF(-1)	0.009003	0.013603	0.661826	0.5139
DIFTENINF(-2)	0.002375	0.014660	0.162020	0.8725
DIFTENINF(-3)	0.006154	0.014323	0.429697	0.6710
DIFTENINF(-4)	-0.000421	0.012937	-0.032508	0.9743
DIFLNGFI	0.605527	2.079814	0.291145	0.7733
DIFLNGFI(-1)	-1.193044	2.496331	-0.477919	0.6367
DIFLNGFI(-2)	1.022882	2.200946	0.464747	0.6460
C	-0.011268	0.070542	-0.159737	0.8743
RESID(-1)	0.368769	0.406752	0.906619	0.3729
RESID(-2)	-0.333478	0.323187	-1.031843	0.3116
RESID(-3)	-0.214057	0.253097	-0.845749	0.4054
RESID(-4)	0.157546	0.255615	0.616341	0.5430

R-squared	0.079448	Mean dependent var	3.42E-17
Adjusted R-squared	-0.487045	S.D. dependent var	0.282551
S.E. of regression	0.344555	Akaike info criterion	0.994471
Sum squared resid	3.086680	Schwarz criterion	1.690759
Log likelihood	-4.381117	Hannan-Quinn criter.	1.251240
F-statistic	0.140246	Durbin-Watson stat	1.783294
Prob(F-statistic)	0.999917		

Table B - 26

Thailand. Model 2. Long run bound test

ARDL Long Run Form and Bounds Test
Dependent Variable: D(TF_BINF)
Selected Model: ARDL(2, 1, 4, 2)
Case 3: Unrestricted Constant and No Trend
Date: 10/19/22 Time: 15:30
Sample: 2018M01 2021M12
Included observations: 43

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.138158	0.058888	2.346101	0.0258
TF_BINF(-1)*	-1.044841	0.191222	-5.464031	0.0000
DIFLNTAPI(-1)	4.220037	2.690010	1.568781	0.1272
DIFTENINF(-1)	0.139451	0.046327	3.010146	0.0053
DIFLNGFI(-1)	-7.517636	3.082842	-2.438541	0.0209
D(TF_BINF(-1))	0.292106	0.157012	1.860401	0.0727
D(DIFLNTAPI)	-1.496581	2.181460	-0.686046	0.4980
D(DIFTENINF)	0.031928	0.011175	2.856976	0.0077
D(DIFTENINF(-1))	-0.084355	0.031576	-2.671490	0.0121
D(DIFTENINF(-2))	-0.040597	0.020471	-1.983204	0.0566
D(DIFTENINF(-3))	-0.017830	0.011600	-1.537071	0.1348
D(DIFLNGFI)	-4.319051	1.957875	-2.205989	0.0352
D(DIFLNGFI(-1))	4.007452	1.979763	2.024208	0.0519

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFLNTAPI	4.038928	2.533329	1.594317	0.1213
DIFTENINF	0.133466	0.050276	2.654651	0.0126
DIFLNGFI	-7.195007	2.907389	-2.474732	0.0192

EC = TF_BINF - (4.0389*DIFLNTAPI + 0.1335*DIFTENINF -7.1950 *DIFLNGFI)

F-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
			Asymptotic: n=1000	
F-statistic	10.01040	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
			Finite Sample: n=45	
Actual Sample Size	43	10%	2.893	3.983
		5%	3.535	4.733
		1%	4.983	6.423
			Finite Sample: n=40	
		10%	2.933	4.02
		5%	3.548	4.803
		1%	5.018	6.61

t-Bounds Test		Null Hypothesis: No levels relationship		
Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-5.464031	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

Thailand. Model 3. Residual's diagnostics and stability

Date: 10/20/22 Time: 14:45
Sample (adjusted): 2018M05 2021M12
Q-statistic probabilities adjusted for 1 dynamic regressor

<table>
<tr><th>Autocorrelation</th><th>Partial Correlation</th><th></th><th>AC</th><th>PAC</th><th>Q-Stat</th><th>Prob*</th></tr>
<tr><td>. | . |</td><td>. | . |</td><td>1</td><td>0.011</td><td>0.011</td><td>0.0054</td><td>0.941</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>2</td><td>-0.160</td><td>-0.160</td><td>1.2351</td><td>0.539</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>3</td><td>0.075</td><td>0.081</td><td>1.5119</td><td>0.680</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>4</td><td>-0.122</td><td>-0.155</td><td>2.2638</td><td>0.687</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>5</td><td>-0.016</td><td>0.018</td><td>2.2776</td><td>0.810</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>6</td><td>0.146</td><td>0.097</td><td>3.4097</td><td>0.756</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>7</td><td>-0.013</td><td>-0.001</td><td>3.4196</td><td>0.844</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>8</td><td>0.108</td><td>0.142</td><td>4.0761</td><td>0.850</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>9</td><td>0.023</td><td>-0.009</td><td>4.1062</td><td>0.904</td></tr>
<tr><td>***| . |</td><td>**| . |</td><td>10</td><td>-0.387</td><td>-0.339</td><td>13.015</td><td>0.223</td></tr>
<tr><td>. | . |</td><td>. |*. |</td><td>11</td><td>0.052</td><td>0.076</td><td>13.180</td><td>0.282</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>12</td><td>0.017</td><td>-0.114</td><td>13.199</td><td>0.355</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>13</td><td>-0.170</td><td>-0.113</td><td>15.089</td><td>0.302</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>14</td><td>0.119</td><td>0.028</td><td>16.039</td><td>0.311</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>15</td><td>0.052</td><td>0.007</td><td>16.227</td><td>0.367</td></tr>
<tr><td>.*| . |</td><td>. | . |</td><td>16</td><td>-0.067</td><td>0.045</td><td>16.556</td><td>0.415</td></tr>
<tr><td>. |*. |</td><td>. |*. |</td><td>17</td><td>0.123</td><td>0.120</td><td>17.683</td><td>0.409</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>18</td><td>-0.038</td><td>0.032</td><td>17.798</td><td>0.469</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>19</td><td>-0.147</td><td>-0.093</td><td>19.550</td><td>0.422</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>20</td><td>-0.010</td><td>-0.192</td><td>19.560</td><td>0.486</td></tr>
</table>

*Probabilities may not be valid for this equation specification.

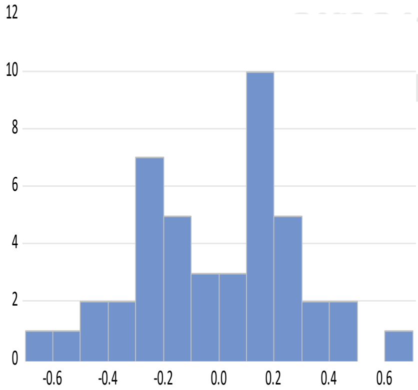
Heteroskedasticity Test: Breusch-Pagan-Godfrey
Null hypothesis: Homoskedasticity

F-statistic	1.401873	Prob. F(9,34)	0.2261
Obs*R-squared	11.90860	Prob. Chi-Square(9)	0.2185
Scaled explained SS	5.610512	Prob. Chi-Square(9)	0.7782

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/20/22 Time: 18:13
Sample: 2018M05 2021M12
Included observations: 44

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.088231	0.016122	5.472728	0.0000
TF_BINF(-1)	-0.038751	0.042062	-0.921284	0.3634
DIFLNTAPROD	-0.030770	0.052270	-0.588676	0.5600
DIFLNTAPROD(-1)	-0.134014	0.054079	-2.478130	0.0183
DIFTENINF	-0.002342	0.003013	-0.777333	0.4423
DIFTENINF(-1)	0.000453	0.002971	0.152419	0.8798
DIFTENINF(-2)	0.001749	0.003123	0.559900	0.5792
DIFTENINF(-3)	0.001293	0.003041	0.425141	0.6734
DIFTER	-0.030883	0.025519	-1.210203	0.2345
DIFTER(-1)	0.027284	0.026329	1.036241	0.3074

R-squared	0.270650	Mean dependent var	0.081519
Adjusted R-squared	0.077587	S.D. dependent var	0.103588
S.E. of regression	0.099488	Akaike info criterion	-1.580836
Sum squared resid	0.336530	Schwarz criterion	-1.175339
Log likelihood	44.77840	Hannan-Quinn criter.	-1.430458
F-statistic	1.401873	Durbin-Watson stat	1.662676
Prob(F-statistic)	0.226058		



Series: Residuals	
Sample 2018M05 2021M12	
Observations 44	
Mean	-2.25e-17
Median	0.051740
Maximum	0.640180
Minimum	-0.652089
Std. Dev.	0.288816
Skewness	-0.190506
Kurtosis	2.578044
Jarque-Bera	0.592564
Probability	0.743578

Variance Inflation Factors
Date: 10/20/22 Time: 18:15
Sample: 2018M01 2021M12
Included observations: 44

Variable	Coefficient Variance	Uncentered VIF	Centered VIF
TF_BINF(-1)	0.018857	1.369976	1.234258
DIFLNTAPROD	0.029120	1.295458	1.295036
DIFLNTAPROD(-1)	0.031170	1.256690	1.252872
DIFTENINF	9.68E-05	1.723727	1.723584
DIFTENINF(-1)	9.41E-05	1.666682	1.666670
DIFTENINF(-2)	0.000104	1.840045	1.839542
DIFTENINF(-3)	9.85E-05	1.672843	1.669922
DIFTER	0.006941	1.168545	1.163025
DIFTER(-1)	0.007389	1.243830	1.234212
C	0.002770	1.155439	NA

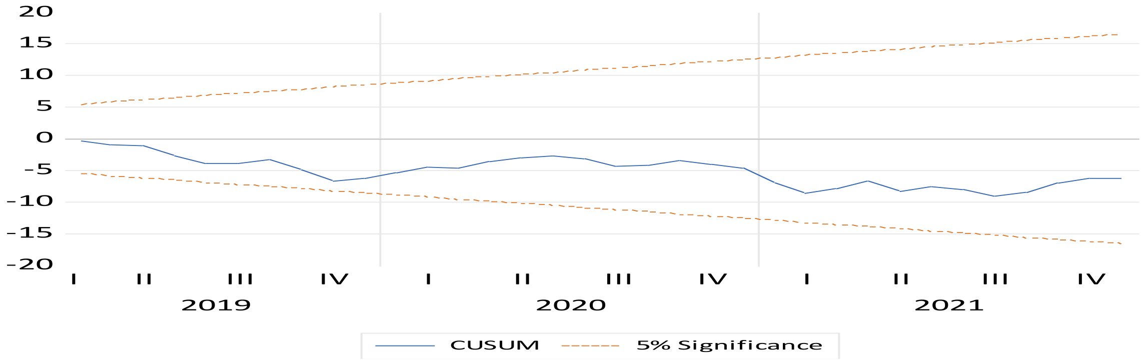


Table B - 27

Thailand. Model 3. Long-Run Bound Test .

ARDL Long Run Form and Bounds Test
Dependent Variable: D(TF_BINF)
Selected Model: ARDL(1, 1, 3, 1)
Case 3: Unrestricted Constant and No Trend
Date: 10/20/22 Time: 18:15
Sample: 2018M01 2021M12
Included observations: 44

Conditional Error Correction Regression

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.063049	0.052634	1.197879	0.2392
TF_BINF(-1)*	-0.697222	0.137320	-5.077361	0.0000
DIFLNTAPROD(-1)	-0.428019	0.286399	-1.494484	0.1443
DIFTENINF(-1)	0.116166	0.029197	3.978700	0.0003
DIFTER(-1)	0.066175	0.120325	0.549968	0.5859
D(DIFLNTAPROD)	-0.065121	0.170647	-0.381609	0.7051
D(DIFTENINF)	0.030326	0.009837	3.082690	0.0041
D(DIFTENINF(-1))	-0.062896	0.016690	-3.768488	0.0006
D(DIFTENINF(-2))	-0.024698	0.009927	-2.488117	0.0179
D(DIFTER)	-0.139590	0.083312	-1.675501	0.1030

Levels Equation
Case 3: Unrestricted Constant and No Trend

Variable	Coefficient	Std. Error	t-Statistic	Prob.
DIFLNTAPROD	-0.613891	0.447533	-1.371722	0.1791
DIFTENINF	0.166613	0.054034	3.083454	0.0040
DIFTER	0.094912	0.175580	0.540565	0.5923

EC = TF_BINF - (-0.6139*DIFLNTAPROD + 0.1666*DIFTENINF + 0.0949 *DIFTER)

F-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
		Asymptotic: n=1000		
F-statistic	12.79867	10%	2.72	3.77
k	3	5%	3.23	4.35
		2.5%	3.69	4.89
		1%	4.29	5.61
		Finite Sample: n=45		
Actual Sample Size	44	10%	2.893	3.983
		5%	3.535	4.733
		1%	4.983	6.423
		Finite Sample: n=40		
		10%	2.933	4.02
		5%	3.548	4.803
		1%	5.018	6.61

t-Bounds Test — Null Hypothesis: No levels relationship

Test Statistic	Value	Signif.	I(0)	I(1)
t-statistic	-5.077361	10%	-2.57	-3.46
		5%	-2.86	-3.78
		2.5%	-3.13	-4.05
		1%	-3.43	-4.37

Table B - 28

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:06
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTIR
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.257074	0.150815	1.704567	0.095
DIFCOI	0.005166	0.004355	1.186273	0.242
DIFTIR	-0.027264	0.681920	-0.039981	0.968
C	0.075968	0.062239	1.220575	0.228

R-squared	0.076953	Mean dependent var	0.10617
Adjusted R-squared	0.012554	S.D. dependent var	0.40053
S.E. of regression	0.398008	Akaike info criterion	1.07657
Sum squared resid	6.811639	Schwarz criterion	1.23403
Log likelihood	-21.29951	Hannan-Quinn criter.	1.13582
F-statistic	1.194940	Durbin-Watson stat	1.96469
Prob(F-statistic)	0.323027		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:07
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.275236	0.149830	1.836986	0.0735
DIFCOI	0.007254	0.004508	1.609013	0.1153
DIFTER	-0.018036	0.092503	-0.194982	0.8464
DIFTER(-1)	0.162074	0.099227	1.633368	0.1100
C	0.074644	0.060706	1.229599	0.2259

R-squared	0.126074	Mean dependent var	0.116957
Adjusted R-squared	0.040813	S.D. dependent var	0.397994
S.E. of regression	0.389788	Akaike info criterion	1.055894
Sum squared resid	6.229321	Schwarz criterion	1.254660
Log likelihood	-19.28557	Hannan-Quinn criter.	1.130353
F-statistic	1.478683	Durbin-Watson stat	1.964771
Prob(F-statistic)	0.226288		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:08
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNCOP LNTEXP DIFTIR
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.193654	0.150362	1.287922	0.2048
LNCOP	0.209623	0.227561	0.921172	0.3622
LNTEXP	0.335746	0.714522	0.469889	0.6409
DIFTIR	-0.027093	0.715691	-0.037855	0.9700
C	-5.778411	10.59833	-0.545219	0.5885

R-squared	0.072858	Mean dependent var	0.106170
Adjusted R-squared	-0.015441	S.D. dependent var	0.400530
S.E. of regression	0.403610	Akaike info criterion	1.123554
Sum squared resid	6.841851	Schwarz criterion	1.320378
Log likelihood	-21.40351	Hannan-Quinn criter.	1.197620
F-statistic	0.825131	Durbin-Watson stat	1.897577
Prob(F-statistic)	0.516645		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:08
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNCOP DIFLNTEXP DIFTIR
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.238661	0.152407	1.565950	0.124
DIFLNCOP	0.383782	0.474356	0.809058	0.423
DIFLNTEXP	0.196735	0.825837	0.238225	0.812
DIFTIR	0.112450	0.715270	0.157213	0.875
C	0.081794	0.063161	1.295018	0.202

R-squared	0.061425	Mean dependent var	0.10617
Adjusted R-squared	-0.027963	S.D. dependent var	0.40053
S.E. of regression	0.406091	Akaike info criterion	1.13581
Sum squared resid	6.926223	Schwarz criterion	1.33263
Log likelihood	-21.69154	Hannan-Quinn criter.	1.20987
F-statistic	0.687174	Durbin-Watson stat	1.95102
Prob(F-statistic)	0.604879		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:09
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNCOP DIFLNTFIMP DIFTER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.262703	0.153771	1.708399	0.0953
DIFLNCOP	0.644097	0.487567	1.321043	0.1940
DIFLNTFIMP	0.195458	0.488248	0.400325	0.6910
DIFTER	0.003460	0.098270	0.035208	0.9721
DIFTER(-1)	0.164015	0.104507	1.569418	0.1244
C	0.076540	0.062237	1.229830	0.2259

R-squared	0.110308	Mean dependent var	0.116957
Adjusted R-squared	-0.000904	S.D. dependent var	0.397994
S.E. of regression	0.398174	Akaike info criterion	1.117253
Sum squared resid	6.341705	Schwarz criterion	1.355771
Log likelihood	-19.69682	Hannan-Quinn criter.	1.206603
F-statistic	0.991871	Durbin-Watson stat	1.953601
Prob(F-statistic)	0.434922		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:12
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNCOP LNTFIMP DIFTER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.208909	0.149808	1.394506	0.1705
LNCOP	0.230855	0.223292	1.033868	0.3071
LNTFIMP	0.186534	0.511443	0.364721	0.7172
DIFTER	-0.051771	0.097978	-0.528392	0.6000
C	-3.504812	7.225256	-0.485078	0.6301

R-squared	0.076580	Mean dependent var	0.106170
Adjusted R-squared	-0.011364	S.D. dependent var	0.400530
S.E. of regression	0.402799	Akaike info criterion	1.119531
Sum squared resid	6.814384	Schwarz criterion	1.316355
Log likelihood	-21.30898	Hannan-Quinn criter.	1.193597
F-statistic	0.870779	Durbin-Watson stat	1.863168
Prob(F-statistic)	0.489463		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:13
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): COP LNTFIMP TER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 2, 3, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.089982	0.169731	0.530146	0.5996
COP	0.009780	0.012894	0.758528	0.4535
COP(-1)	0.013209	0.020835	0.633985	0.5305
COP(-2)	-0.025047	0.012737	-1.966436	0.0577
LNTFIMP	0.785616	0.584550	1.343967	0.1881
LNTFIMP(-1)	0.062208	0.594230	0.104686	0.9173
LNTFIMP(-2)	-1.181733	0.591392	-1.998225	0.0540
LNTFIMP(-3)	-1.011811	0.636431	-1.589821	0.1214
TER	0.070992	0.108044	0.657065	0.5157
TER(-1)	0.262476	0.131406	1.997441	0.0541
TER(-2)	-0.153155	0.110115	-1.390872	0.1736
C	13.63898	10.02177	1.360936	0.1828

R-squared	0.352125	Mean dependent var	0.125778
Adjusted R-squared	0.136166	S.D. dependent var	0.397918
S.E. of regression	0.369835	Akaike info criterion	1.071661
Sum squared resid	4.513681	Schwarz criterion	1.553438
Log likelihood	-12.11237	Hannan-Quinn criter.	1.251262
F-statistic	1.630521	Durbin-Watson stat	1.647583
Prob(F-statistic)	0.135653		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:10
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNCOP LNTFIMP DIFTER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.208909	0.149808	1.394506	0.1705
LNCOP	0.230855	0.223292	1.033868	0.3071
LNTFIMP	0.186534	0.511443	0.364721	0.7172
DIFTER	-0.051771	0.097978	-0.528392	0.6000
C	-3.504812	7.225256	-0.485078	0.6301

R-squared	0.076580	Mean dependent var	0.106170
Adjusted R-squared	-0.011364	S.D. dependent var	0.400530
S.E. of regression	0.402799	Akaike info criterion	1.119531
Sum squared resid	6.814384	Schwarz criterion	1.316355
Log likelihood	-21.30898	Hannan-Quinn criter.	1.193597
F-statistic	0.870779	Durbin-Watson stat	1.863168
Prob(F-statistic)	0.489463		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:14
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFLNTFIMP DIFTER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.291820	0.154724	1.886070	0.0666
DIFCOI	0.007738	0.004649	1.664337	0.1039
DIFLNTFIMP	0.245192	0.484829	0.505729	0.6158
DIFTER	-0.007483	0.095658	-0.078225	0.9380
DIFTER(-1)	0.168153	0.100859	1.667212	0.1033
C	0.070658	0.061770	1.143896	0.2595

R-squared	0.131626	Mean dependent var	0.116957
Adjusted R-squared	0.023080	S.D. dependent var	0.397994
S.E. of regression	0.393375	Akaike info criterion	1.092999
Sum squared resid	6.189744	Schwarz criterion	1.331517
Log likelihood	-19.13898	Hannan-Quinn criter.	1.182349
F-statistic	1.212625	Durbin-Watson stat	1.976785
Prob(F-statistic)	0.320931		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:14
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.275236	0.149830	1.836986	0.0735
DIFCOI	0.007254	0.004508	1.609013	0.1153
DIFTER	-0.018036	0.092503	-0.194982	0.8464
DIFTER(-1)	0.162074	0.099227	1.633368	0.1100
C	0.074644	0.060706	1.229599	0.2259

R-squared	0.126074	Mean dependent var	0.116957
Adjusted R-squared	0.040813	S.D. dependent var	0.397994
S.E. of regression	0.389788	Akaike info criterion	1.055894
Sum squared resid	6.229321	Schwarz criterion	1.254660
Log likelihood	-19.28557	Hannan-Quinn criter.	1.130353
F-statistic	1.478683	Durbin-Watson stat	1.964771
Prob(F-statistic)	0.226288		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:15
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTLEI DIFTNEER
Fixed regressors: C
Number of models evaluated: 500
Selected Model: ARDL(1, 0, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.258563	0.153178	1.687994	0.0988
DIFCOI	0.004753	0.004692	1.013052	0.3168
DIFTLEI	-0.019284	0.052379	-0.368160	0.7146
DIFTNEER	-0.004935	0.046878	-0.105279	0.9167
C	0.080989	0.062343	1.299096	0.2010

R-squared	0.080411	Mean dependent var	0.106170
Adjusted R-squared	-0.007169	S.D. dependent var	0.400530
S.E. of regression	0.401963	Akaike info criterion	1.115374
Sum squared resid	6.786117	Schwarz criterion	1.312199
Log likelihood	-21.21130	Hannan-Quinn criter.	1.189441
F-statistic	0.918144	Durbin-Watson stat	1.960667
Prob(F-statistic)	0.462382		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:17
Sample (adjusted): 2018M02 2021M07
Included observations: 42 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTLEI DIFCOI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.188187	0.163509	1.150923	0.2570
DIFLNTLEI	-0.000171	0.000167	-1.023137	0.3127
DIFCOI	0.002628	0.004510	0.582720	0.5635
C	126.1712	123.2510	1.023694	0.3125

R-squared	0.064314	Mean dependent var	0.088095
Adjusted R-squared	-0.009556	S.D. dependent var	0.392473
S.E. of regression	0.394344	Akaike info criterion	1.067207
Sum squared resid	5.909279	Schwarz criterion	1.232700
Log likelihood	-18.41136	Hannan-Quinn criter.	1.127867
F-statistic	0.870632	Durbin-Watson stat	1.982756
Prob(F-statistic)	0.464769		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:18
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.275236	0.149830	1.836986	0.0735
DIFCOI	0.007254	0.004508	1.609013	0.1153
DIFTER	-0.018036	0.092503	-0.194982	0.8464
DIFTER(-1)	0.162074	0.099227	1.633368	0.1100
C	0.074644	0.060706	1.229599	0.2259

R-squared	0.126074	Mean dependent var	0.116957
Adjusted R-squared	0.040813	S.D. dependent var	0.397994
S.E. of regression	0.389788	Akaike info criterion	1.055894
Sum squared resid	6.229321	Schwarz criterion	1.254660
Log likelihood	-19.28557	Hannan-Quinn criter.	1.130353
F-statistic	1.478683	Durbin-Watson stat	1.964771
Prob(F-statistic)	0.226288		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:16
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTNEER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.259496	0.151609	1.711612	0.0942
DIFCOI	0.005300	0.004405	1.202990	0.2356
DIFTNEER	-0.007197	0.046004	-0.156436	0.8764
C	0.076274	0.060396	1.262884	0.2134

R-squared	0.077443	Mean dependent var	0.106170
Adjusted R-squared	0.013079	S.D. dependent var	0.400530
S.E. of regression	0.397902	Akaike info criterion	1.076043
Sum squared resid	6.808017	Schwarz criterion	1.233503
Log likelihood	-21.28701	Hannan-Quinn criter.	1.135296
F-statistic	1.203200	Durbin-Watson stat	1.969259
Prob(F-statistic)	0.320021		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:20
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOP DIFTAPI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.290543	0.154373	1.882090	0.0673
DIFCOP	0.011134	0.010020	1.111252	0.2733
DIFTAPI	-0.008378	0.015735	-0.532452	0.5974
DIFTAPI(-1)	0.035759	0.015996	2.235446	0.0312
DIFTAPI(-2)	-0.030605	0.016278	-1.880175	0.0676
C	0.086113	0.059410	1.449469	0.1552

R-squared	0.201952	Mean dependent var	0.125778
Adjusted R-squared	0.099638	S.D. dependent var	0.397918
S.E. of regression	0.377574	Akaike info criterion	1.013465
Sum squared resid	5.559919	Schwarz criterion	1.254353
Log likelihood	-16.80296	Hannan-Quinn criter.	1.103266
F-statistic	1.973848	Durbin-Watson stat	1.812540
Prob(F-statistic)	0.104180		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:22
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTIR LNTAPROD
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 1)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.187137	0.147457	1.269091	0.2114
DIFLNTIR	0.533530	0.685300	0.778535	0.4406
LNTAPROD	-0.122173	0.218167	-0.559998	0.5785
LNTAPROD(-1)	-0.292253	0.223281	-1.308901	0.1977
C	2.134260	1.214939	1.756682	0.0863

R-squared	0.112809	Mean dependent var	0.106170
Adjusted R-squared	0.028314	S.D. dependent var	0.400530
S.E. of regression	0.394819	Akaike info criterion	1.079508
Sum squared resid	6.547039	Schwarz criterion	1.276333
Log likelihood	-20.36845	Hannan-Quinn criter.	1.153575
F-statistic	1.335100	Durbin-Watson stat	1.880959
Prob(F-statistic)	0.272812		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:22
Sample (adjusted): 2018M05 2021M12
Included observations: 44 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTIR DIFTENINF
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.235876	0.151635	1.555543	0.1283
DIFLNTIR	0.166299	0.661930	0.251234	0.8030
DIFTENINF	0.020624	0.010471	1.969615	0.0564
DIFTENINF(-1)	0.019989	0.011011	1.815319	0.0776
DIFTENINF(-2)	0.028534	0.010823	2.636510	0.0122
DIFTENINF(-3)	0.019146	0.010782	1.775827	0.0840
C	0.076781	0.060444	1.270284	0.2119

R-squared	0.233257	Mean dependent var	0.110909
Adjusted R-squared	0.108921	S.D. dependent var	0.389668
S.E. of regression	0.367835	Akaike info criterion	0.982544
Sum squared resid	5.006188	Schwarz criterion	1.266392
Log likelihood	-14.61597	Hannan-Quinn criter.	1.087809
F-statistic	1.876015	Durbin-Watson stat	2.084315
Prob(F-statistic)	0.111131		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:19
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFTAPI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.290205	0.153720	1.887879	0.0665
DIFCOI	0.005000	0.004287	1.166325	0.2506
DIFTAPI	-0.008296	0.015685	-0.528924	0.5999
DIFTAPI(-1)	0.035913	0.015969	2.248903	0.0302
DIFTAPI(-2)	-0.030364	0.016266	-1.866720	0.0695
C	0.085351	0.059358	1.437905	0.1584

R-squared	0.204432	Mean dependent var	0.125778
Adjusted R-squared	0.102436	S.D. dependent var	0.397918
S.E. of regression	0.376987	Akaike info criterion	1.010352
Sum squared resid	5.542640	Schwarz criterion	1.251240
Log likelihood	-16.73292	Hannan-Quinn criter.	1.100153
F-statistic	2.004318	Durbin-Watson stat	1.813287
Prob(F-statistic)	0.099468		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:26
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNTNEER LNTAPI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(2, 0, 3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.185881	0.155626	1.194409	0.2399
TF_BINF(-2)	-0.295809	0.139199	-2.125083	0.0403
LNTNEER	-2.440547	1.761909	-1.385172	0.1743
LNTAPI	-0.972936	2.173249	-0.447687	0.6570
LNTAPI(-1)	5.075165	3.327150	1.525379	0.1357
LNTAPI(-2)	-8.770598	3.322603	-2.639677	0.0121
LNTAPI(-3)	2.807413	2.249461	1.248038	0.2199
C	20.91162	9.795790	2.134756	0.0395

R-squared	0.324010	Mean dependent var	0.125778
Adjusted R-squared	0.196121	S.D. dependent var	0.397918
S.E. of regression	0.356770	Akaike info criterion	0.936363
Sum squared resid	4.709550	Schwarz criterion	1.257547
Log likelihood	-13.06816	Hannan-Quinn criter.	1.056097
F-statistic	2.533510	Durbin-Watson stat	1.951805
Prob(F-statistic)	0.031012		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:24
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTNEER LNTAPI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(2, 1, 3)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.234297	0.148883	1.573702	0.1243
TF_BINF(-2)	-0.279469	0.137332	-2.034995	0.0493
DIFTNEER	0.038634	0.047379	0.815420	0.4202
DIFTNEER(-1)	-0.092640	0.048006	-1.929748	0.0615
LNTAPI	-1.356083	2.108745	-0.643076	0.5242
LNTAPI(-1)	6.509988	3.464649	1.878975	0.0684
LNTAPI(-2)	-11.69219	3.544066	-3.299090	0.0022
LNTAPI(-3)	4.305915	2.241659	1.920861	0.0627
C	11.03689	5.604688	1.969225	0.0567

R-squared	0.356410	Mean dependent var	0.125778
Adjusted R-squared	0.213390	S.D. dependent var	0.397918
S.E. of regression	0.352917	Akaike info criterion	0.931691
Sum squared resid	4.483823	Schwarz criterion	1.293023
Log likelihood	-11.96304	Hannan-Quinn criter.	1.066392
F-statistic	2.492033	Durbin-Watson stat	1.995741
Prob(F-statistic)	0.028980		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:27
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNTNEER LNTAPROD
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.199466	0.147455	1.352718	0.1832
LNTNEER	-1.309769	1.759718	-0.744306	0.4607
LNTAPROD	-0.203204	0.200341	-1.014293	0.3161
C	7.351959	8.430968	0.872018	0.3880

R-squared	0.081558	Mean dependent var	0.106170
Adjusted R-squared	0.017480	S.D. dependent var	0.400530
S.E. of regression	0.397014	Akaike info criterion	1.071573
Sum squared resid	6.777654	Schwarz criterion	1.229033
Log likelihood	-21.18197	Hannan-Quinn criter.	1.130826
F-statistic	1.272803	Durbin-Watson stat	1.954079
Prob(F-statistic)	0.295720		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:29
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTNEER TENINF
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.248615	0.143398	1.733740	0.090
DIFLNTNEER	-0.124242	5.212237	-0.023837	0.981
TENINF	0.024184	0.011802	2.049122	0.046
C	0.075420	0.058445	1.290439	0.203

R-squared	0.131639	Mean dependent var	0.10617
Adjusted R-squared	0.071056	S.D. dependent var	0.40053
S.E. of regression	0.386038	Akaike info criterion	1.01550
Sum squared resid	6.408080	Schwarz criterion	1.17296
Log likelihood	-19.86430	Hannan-Quinn criter.	1.07475
F-statistic	2.172856	Durbin-Watson stat	1.99081
Prob(F-statistic)	0.105067		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:29
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTNEER DIFLNTEXP
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.213698	0.149174	1.432535	0.1592
DIFTNEER	0.005444	0.046485	0.117123	0.9073
DIFLNTEXP	-0.055675	0.753655	-0.073874	0.9415
C	0.083509	0.061137	1.365925	0.1791

R-squared	0.046515	Mean dependent var	0.106170
Adjusted R-squared	-0.020007	S.D. dependent var	0.400530
S.E. of regression	0.404517	Akaike info criterion	1.109018
Sum squared resid	7.036251	Schwarz criterion	1.266477
Log likelihood	-22.06192	Hannan-Quinn criter.	1.168271
F-statistic	0.699243	Durbin-Watson stat	1.897179
Prob(F-statistic)	0.557667		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:30
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTNEER DIFLNTFIMP
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.218991	0.151026	1.450028	0.1543
DIFTNEER	0.005196	0.045573	0.114006	0.9098
DIFLNTFIMP	0.107144	0.478006	0.224148	0.8237
C	0.082421	0.061221	1.346279	0.1853

R-squared	0.047507	Mean dependent var	0.106170
Adjusted R-squared	-0.018946	S.D. dependent var	0.400530
S.E. of regression	0.404306	Akaike info criterion	1.107977
Sum squared resid	7.028932	Schwarz criterion	1.265436
Log likelihood	-22.03746	Hannan-Quinn criter.	1.167230
F-statistic	0.714898	Durbin-Watson stat	1.905485
Prob(F-statistic)	0.548496		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:31
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTAPROD DIFLNTFIMP
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 1, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.226574	0.149725	1.513270	0.1379
DIFLNTAPROD	-0.052273	0.196517	-0.265995	0.7916
DIFLNTAPROD(-1)	-0.356251	0.205346	-1.734877	0.0903
DIFLNTFIMP	0.044279	0.466182	0.094982	0.9248
C	0.097522	0.060420	1.614069	0.1142

R-squared	0.110854	Mean dependent var	0.116957
Adjusted R-squared	0.024108	S.D. dependent var	0.397994
S.E. of regression	0.393167	Akaike info criterion	1.073160
Sum squared resid	6.337807	Schwarz criterion	1.271925
Log likelihood	-19.68267	Hannan-Quinn criter.	1.147618
F-statistic	1.277920	Durbin-Watson stat	1.919623
Prob(F-statistic)	0.294324		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:32
Sample (adjusted): 2018M03 2021M12
Included observations: 46 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNTAPROD DIFLNTEXP
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 1, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.224120	0.146907	1.525586	0.1348
DIFLNTAPROD	-0.048489	0.194866	-0.248831	0.8047
DIFLNTAPROD(-1)	-0.380059	0.207839	-1.828620	0.0747
DIFLNTEXP	-0.454817	0.732759	-0.620691	0.5382
C	0.100275	0.060058	1.669633	0.1026

R-squared	0.118938	Mean dependent var	0.116957
Adjusted R-squared	0.032980	S.D. dependent var	0.397994
S.E. of regression	0.391376	Akaike info criterion	1.064027
Sum squared resid	6.280190	Schwarz criterion	1.262793
Log likelihood	-19.47262	Hannan-Quinn criter.	1.138486
F-statistic	1.383683	Durbin-Watson stat	1.908126
Prob(F-statistic)	0.256431		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:28
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): LNTNEER TENINF
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.234085	0.143425	1.632104	0.1100
LNTNEER	-1.292117	1.698241	-0.760856	0.4509
TENINF	0.023871	0.011656	2.048018	0.0467
C	6.261304	8.130344	0.770116	0.4454

R-squared	0.143163	Mean dependent var	0.106170
Adjusted R-squared	0.083384	S.D. dependent var	0.400530
S.E. of regression	0.383468	Akaike info criterion	1.002142
Sum squared resid	6.323039	Schwarz criterion	1.159602
Log likelihood	-19.55034	Hannan-Quinn criter.	1.061395
F-statistic	2.394855	Durbin-Watson stat	1.984758
Prob(F-statistic)	0.081402		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:34
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): TENINF LNTFIMP
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.255402	0.143467	1.780212	0.0821
TENINF	0.024122	0.011696	2.062444	0.0452
LNTFIMP	0.235836	0.484552	0.486709	0.6289
C	-3.280367	6.895141	-0.475751	0.6367

R-squared	0.136385	Mean dependent var	0.106170
Adjusted R-squared	0.076133	S.D. dependent var	0.400530
S.E. of regression	0.384981	Akaike info criterion	1.010021
Sum squared resid	6.373056	Schwarz criterion	1.167481
Log likelihood	-19.73550	Hannan-Quinn criter.	1.069274
F-statistic	2.263569	Durbin-Watson stat	1.976649
Prob(F-statistic)	0.094653		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:34
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFLNCOP DIFLNGFI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.271712	0.144361	1.882164	0.0666
DIFLNCOP	0.811575	0.472317	1.718283	0.0929
DIFLNGFI	-4.677377	2.257473	-2.071953	0.0443
C	0.100861	0.058806	1.715168	0.0935

R-squared	0.145286	Mean dependent var	0.106170
Adjusted R-squared	0.085655	S.D. dependent var	0.400530
S.E. of regression	0.382992	Akaike info criterion	0.999661
Sum squared resid	6.307371	Schwarz criterion	1.157120
Log likelihood	-19.49204	Hannan-Quinn criter.	1.058914
F-statistic	2.436410	Durbin-Watson stat	1.917992
Prob(F-statistic)	0.077614		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:35
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFCOI DIFGFI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.302104	0.144761	2.086911	0.0429
DIFCOI	0.008996	0.004439	2.026867	0.0489
DIFGFI	-0.042972	0.019911	-2.158180	0.0365
C	0.097802	0.058194	1.680610	0.1001

R-squared	0.167134	Mean dependent var	0.106170
Adjusted R-squared	0.109027	S.D. dependent var	0.400530
S.E. of regression	0.378066	Akaike info criterion	0.973767
Sum squared resid	6.146144	Schwarz criterion	1.131227
Log likelihood	-18.88353	Hannan-Quinn criter.	1.033020
F-statistic	2.876316	Durbin-Watson stat	1.943178
Prob(F-statistic)	0.046991		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:36
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTLEI DIFCOI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.256838	0.150537	1.706141	0.0952
DIFTLEI	-0.020006	0.051327	-0.389785	0.6986
DIFCOI	0.004620	0.004467	1.034368	0.3067
C	0.081366	0.061520	1.322605	0.1930

R-squared	0.080168	Mean dependent var	0.106170
Adjusted R-squared	0.015994	S.D. dependent var	0.400530
S.E. of regression	0.397314	Akaike info criterion	1.073085
Sum squared resid	6.787908	Schwarz criterion	1.230544
Log likelihood	-21.21750	Hannan-Quinn criter.	1.132338
F-statistic	1.249227	Durbin-Watson stat	1.957644
Prob(F-statistic)	0.303749		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:37
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTLEI DIFTIR
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.221838	0.148515	1.493708	0.1426
DIFTLEI	-0.035697	0.051490	-0.693274	0.4919
DIFTIR	-0.002529	0.701647	-0.003605	0.9971
C	0.090604	0.062698	1.445083	0.1557

R-squared	0.057281	Mean dependent var	0.106170
Adjusted R-squared	-0.008490	S.D. dependent var	0.400530
S.E. of regression	0.402226	Akaike info criterion	1.097662
Sum squared resid	6.956801	Schwarz criterion	1.255121
Log likelihood	-21.79506	Hannan-Quinn criter.	1.156915
F-statistic	0.870923	Durbin-Watson stat	1.901043
Prob(F-statistic)	0.463564		

*Note: p-values and any subsequent tests do not account for model selection.

Thailand model's attempt

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:38
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTLEI DIFTNEER
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.220704	0.148594	1.485279	0.1448
DIFTLEI	-0.036081	0.049700	-0.725973	0.4718
DIFTNEER	0.007836	0.045165	0.173497	0.8631
C	0.090821	0.061602	1.474330	0.1477

R-squared	0.057941	Mean dependent var	0.106170
Adjusted R-squared	-0.007784	S.D. dependent var	0.400530
S.E. of regression	0.402086	Akaike info criterion	1.096963
Sum squared resid	6.951937	Schwarz criterion	1.254422
Log likelihood	-21.77862	Hannan-Quinn criter.	1.156216
F-statistic	0.881561	Durbin-Watson stat	1.899223
Prob(F-statistic)	0.458200		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:33
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): TENINF LNTEXP
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.234919	0.142880	1.644166	0.1074
TENINF	0.025340	0.011718	2.162422	0.0362
LNTEXP	0.566919	0.674318	0.840730	0.4052
C	-8.386754	10.06546	-0.833221	0.4093

R-squared	0.145671	Mean dependent var	0.106170
Adjusted R-squared	0.086066	S.D. dependent var	0.400530
S.E. of regression	0.382906	Akaike info criterion	0.999211
Sum squared resid	6.304532	Schwarz criterion	1.156670
Log likelihood	-19.48146	Hannan-Quinn criter.	1.058464
F-statistic	2.443960	Durbin-Watson stat	1.996491
Prob(F-statistic)	0.076945		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:39
Sample (adjusted): 2018M04 2021M12
Included observations: 45 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTLEI DIFTAPI
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 2)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.253531	0.152641	1.660963	0.1047
DIFTLEI	-0.017153	0.052735	-0.325265	0.7467
DIFTAPI	-0.003499	0.017202	-0.203432	0.8399
DIFTAPI(-1)	0.031059	0.016334	1.901503	0.0646
DIFTAPI(-2)	-0.033696	0.016265	-2.071674	0.0450
C	0.096377	0.060509	1.592776	0.1193

R-squared	0.178910	Mean dependent var	0.125778
Adjusted R-squared	0.073642	S.D. dependent var	0.397918
S.E. of regression	0.382986	Akaike info criterion	1.041928
Sum squared resid	5.720448	Schwarz criterion	1.282817
Log likelihood	-17.44339	Hannan-Quinn criter.	1.131729
F-statistic	1.699571	Durbin-Watson stat	1.792402
Prob(F-statistic)	0.157654		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:40
Sample (adjusted): 2018M02 2021M12
Included observations: 47 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTLEI TENINF
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 0)
Note: final equation sample is larger than selection sample

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.255077	0.142610	1.788633	0.0807
DIFTLEI	-0.033739	0.047387	-0.711991	0.4803
TENINF	0.023990	0.011662	2.057134	0.0458
C	0.082447	0.058925	1.399196	0.1689

R-squared	0.141745	Mean dependent var	0.106170
Adjusted R-squared	0.081867	S.D. dependent var	0.400530
S.E. of regression	0.383785	Akaike info criterion	1.003795
Sum squared resid	6.333499	Schwarz criterion	1.161254
Log likelihood	-19.58918	Hannan-Quinn criter.	1.063048
F-statistic	2.367229	Durbin-Watson stat	1.989316
Prob(F-statistic)	0.084025		

*Note: p-values and any subsequent tests do not account for model selection.

Dependent Variable: TF_BINF
Method: ARDL
Date: 10/21/22 Time: 10:40
Sample (adjusted): 2018M06 2021M12
Included observations: 43 after adjustments
Maximum dependent lags: 4 (Automatic selection)
Model selection method: Akaike info criterion (AIC)
Dynamic regressors (4 lags, automatic): DIFTLEI DIFTAPROD
Fixed regressors: C
Number of models evaluated: 100
Selected Model: ARDL(1, 0, 4)

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
TF_BINF(-1)	0.222930	0.153328	1.453940	0.1549
DIFTLEI	0.054502	0.054707	0.996251	0.3260
DIFTAPROD	-0.000210	0.000962	-0.218177	0.8286
DIFTAPROD(-1)	-0.001669	0.001086	-1.537340	0.1332
DIFTAPROD(-2)	-0.000167	0.001178	-0.141906	0.8880
DIFTAPROD(-3)	-0.001378	0.001161	-1.186905	0.2433
DIFTAPROD(-4)	-0.002875	0.001164	-2.469758	0.0185
C	0.070343	0.060227	1.167977	0.2507

R-squared	0.250584	Mean dependent var	0.103023
Adjusted R-squared	0.100700	S.D. dependent var	0.390711
S.E. of regression	0.370517	Akaike info criterion	1.018404
Sum squared resid	4.804889	Schwarz criterion	1.346069
Log likelihood	-13.89568	Hannan-Quinn criter.	1.139237
F-statistic	1.671858	Durbin-Watson stat	1.807598
Prob(F-statistic)	0.148252		

*Note: p-values and any subsequent tests do not account for model selection.

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