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CREDIT RATIONING: SOME INTERNATIONAL EVIDENCE

by

Kamogelo M Thokwane

Student Number 820722

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Supervisor: Professor Christopher Malikane

ABSTRACT

This study was prompted by the consumer financial distress in South Africa in recent years, characterized by skyrocketing interest rates. It was thus important to understand how the South African Credit Market works. Namely, how credit supply and demand interact over time, and what drives them. Moreover, it was important to understand how the credit market of South Africa as an emerging economy compares to the credit market of an advanced economy such as the United States of America. The end goal was to determine whether credit was restricted in South Africa, and if so, how much more or less than in the USA.

To achieve the above goal, credit supply and demand models were estimated for each country as functions of real interest rate, real GDP, and real House Price Index. The models were estimated using the Two Stage Least Squares regression technique. It was found that only the real GDP was statistically significant in explaining credit supply and demand for both countries. Moreover, it was found that no significant restriction of credit was present for both countries over the observation period, contrary to what the literature says.

Key Words: Information asymmetry, Credit rationing, Adverse selection, Moral hazard

DEDICATION

I dedicate this thesis and my MMFI degree to my family, to whom I am eternally grateful, and without whom I could not have achieved this great milestone.

- My wife, Mathapelo Thokwane, thanks for your understanding through the late nights and time away from you in pursuit of this qualification. Thanks for your love and support, I could not have done it without you.
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1 Introduction

1.1 Background

The credit market consists of borrowers and lenders of funds. As outlined by Dick & Lehnert (2010) and Bernanke (1992), borrowers have a net deficit of funds while lenders have a net surplus. Thus, borrowers are on the demand side of the credit market while lenders are on the supply side. In a perfect credit market, supply and demand would adjust dynamically through interest rate adjustments (Doraszelski, Lewis & Pakes (2018); Arrow & Debreu (1954)). Should supply exceed demand, for instance, interest rates would decrease until the market reaches equilibrium (Elegido (2015), Jaffee & Russell (1976), Stiglitz & Weiss (1981)). However, Jaffee & Russell (1976) note that this does not occur in real credit markets. That is, real credit markets are imperfect.

Whenever a lender extends credit to a borrower, the lender expects the borrower to fully repay the borrowed funds plus any interest charged. To achieve this, the lender needs to gather relevant information about the borrower and use this information to determine their likelihood of repaying (Stiglitz & Weiss (1981)). However, as Bernanke (1992) outlines, there is a limit on the quality and completeness of the information that the lender can gather about the borrower. A consequence of this is that the borrower always has more credit-relevant information about themselves than the lender. That is, the credit market has inherent information asymmetry between the borrower and the lender.

Further, Stiglitz & Weiss (1981) detail that due to the inherent information asymmetry in the credit market, the interest rate fails to clear the market due to adverse selection and incentive phenomena. Stiglitz & Weiss (1981) further show that the inherent information asymmetry causes the credit market to exist in a state of Walrasian disequilibrium where credit supply is below credit demand, which is called credit rationing.

This study aims to characterize credit rationing in emerging and advanced economies. South Africa represents emerging markets, while the United States of America represents advanced markets. In addition to serving as a representative for advanced markets, including the USA in the study also serves to paint an international picture of credit rationing. Furthermore, the inclusion of the South African credit market in the study contributes to the relevance of the study, since this may contribute to a better understanding of the market, and potentially inform policies that can improve it.

1.2 Research Questions

There are two questions which this research project seeks to answer:

a. Does credit rationing exist in emerging and advanced markets?
b. What are the factors that determine the level of credit rationing in emerging and advanced markets?

1.3 Research Objectives

The objectives of this study are:

a. To statistically determine whether credit rationing exists in emerging and advanced markets.
b. To find the determinants of credit rationing in emerging and advanced markets.

1.4 Research Hypotheses

Null hypothesis: There is no credit rationing.

Alternative hypothesis: There is credit rationing.

1.5 Research Significance

This study explores factors that affect credit rationing and estimation of credit rationing from an empirical perspective, in the context of emerging and advanced markets. This will help further develop an understanding of how credit markets work, both from developing and advanced markets perspectives.

In addition, this study is relevant to the local South African credit market since South Africa is one of the countries used in this study. This is significant because it aligns with efforts to explore academic solutions for our economic challenges. Therefore, this study may help inform future policymaking to address some of the credit market-related challenges in South Africa.

1.6 Research Limitations

This research was based on two countries (RSA and USA) as the sample countries for Emerging and advanced economies respectively.

2 Literature Review

2.1 Brief Description of Key Concepts

2.1.1 Information Asymmetry

Information asymmetry in credit markets refers to the phenomenon where borrowers know more about their credit-relevant information than lenders do (Bernanke, 1992). This phenomenon may occur because of the cost of gathering information about borrowers, due to borrowers withholding credit-relevant information to maximize their probability of accessing credit, or a combination of both.

2.1.2 Adverse Selection

Adverse selection in credit markets occurs when the quality of borrowers taking on credit deteriorates as interest rates increase (Stiglitz & Weiss, 1981). This occurs because borrowers of poor creditworthiness are more likely to accept higher interest rates than borrowers with good creditworthiness. Thus, if the lender keeps offering credit at higher and higher interest rates, eventually the only borrowers who will take on the credit will be borrowers with poor creditworthiness (Stiglitz & Weiss, 1981).

2.1.3 Moral Hazard

Moral hazard in credit markets refers to when borrowers invest in excessively risky projects because the lender cannot monitor their investment activities (Stiglitz & Weiss, 1981). This situation is more likely to happen when the borrower is charged high interest rates due to poor creditworthiness. Due to the higher cost of credit, the borrower may aim to maximize returns on investments, thus taking on excessively risky projects (Bernanke, 1992). Moral hazard manifests especially when the borrower has little or nothing to lose if the risky project fails. Thus, lenders tend to structure credit agreements such that borrowers attach some assets as collateral in case of default. Collateral thus acts to reduce moral hazard (Stiglitz & Weiss,1981;Bernanke, 1992).

2.2 Credit Rationing

Credit rationing refers to a situation where borrowers are unable to access credit or can only obtain amounts lower than what they request from lenders, even though they are willing to pay the prevailing interest rate (Stiglitz & Weiss, 1981; Medhi et al., 2020; Ying, 2022).

2.2.1 Earlier work: information asymmetry, adverse selection, and moral hazard.

Until the early 1990s, credit rationing was largely understood in terms of information asymmetry and adverse selection. This understanding of credit rationing was pioneered in the seminal works of Akerlof (1970), Rothschild & Stiglitz (1976), Wilson (1977), and Stiglitz and Weis (1981). Akerlof (1970) introduced the concept of adverse selection due to information asymmetry. He showed how when sellers know more about the quality of their goods than buyers, buyers become hesitant to pay high prices fearing that they might receive a lower-quality product. He further

showed how that may result in a market dominated by lower-quality goods, which has significant implications for market efficiency.

Rothschild and Stiglitz (1976) built on Akerlof's work by considering insurance markets. They demonstrated how insurers' inability to distinguish between high and low-risk individuals due to incomplete risk information leads to adverse selection, higher insurance premiums, and ultimately market failure. Stiglitz and Weiss (1981) expanded the analysis from insurance markets to credit markets. They explored how lenders' inability to assess borrowers' true credit risk can lead to credit rationing. In addition to information asymmetry and adverse selection, they also showed that moral hazard plays a key role in credit rationing. They developed a model that emphasizes that lenders might deny credit-worthy borrowers access to credit due to information costs. More recent work expanding on this theme include Yi (2018) and Benjamin (2022).

2.2.2 Subsequent work: The credit channel and monetary policy transmission

In the early 1990s, the understanding of credit rationing was further developed to consider how monetary policy changes affect the credit market. This line of thinking was pioneered through the works of Gertler and Gilchrist (1994), and Bernanke and Gertler (1995). In Gertler and Gilchrist's 1994 work, they investigated how monetary policy shocks impact the behavior of small manufacturing firms. They concluded that changes in monetary policy affect firms' investment decisions and overall financial performance. Their work highlighted the significance of credit rationing in amplifying the effects of monetary policy changes on the economy.

Building on Gertler and Gilchrist (1994), Bernanke and Gertler's 1995 seminal paper delved into how monetary policy changes affect the availability of credit and how that affects the economy at large. The authors proposed a mechanism through which monetary policy affects the cost of credit, bank lending, and firm investment decisions. This paper highlighted how credit availability and lending behavior play a crucial role in transmitting monetary policy changes to the broader economy. Recent research by Bosshardt et al. (2024) examines how tighter monetary policy affects the economy via the mortgage market.

2.2.3 Current thinking: Behavioral economics approach

While research on information asymmetry and monetary policy is still active, recent developments in the thinking around credit rationing focus more on understanding the role that human behavior[1] and psychology have on credit rationing. A couple of key and independent works are reviewed below.

Karlan and Zinman (2009) investigated the role of information asymmetry and human biases in the credit market. In their study, they compared borrowers' creditworthiness according to the borrowers, and borrowers' creditworthiness as extracted from credit bureaus. A key insight gleaned from their investigation is that borrowers overestimate their creditworthiness, which influences their borrowing decisions. That is, borrowers are systematically biased concerning their

[1] Though this perspective has gained increasing research interest in recent years, Thaler (2016) argues that this perspective is a rediscovery of the early ideas of Adam Smith, Irving Fisher, and John Keynes.

creditworthiness. From this insight, they suggested that if borrowers have better access to their credit information, then credit rationing might be reduced.

2.2.4 Future trends: Network effects and AI

Some researchers have explored the role of social media networks and peer interactions in the credit market. The idea is to explore the information sharing and reputation building that can occur through social media networks, and how these might help reduce information asymmetry and thus curb credit rationing. A key lever in this field of research is AI, which helps in processing and making sense of big and unstructured data. Some notable works in this field include Yang et al. (2022) and Zhang et al. (2016).

2.3 Evidence of Credit Rationing: International Perspective

Bernanke (1992) argues that the existence of information gathering, analysis, and monitoring in credit markets is a direct consequence of inherent information asymmetry. As described in section 2.2, inherent information asymmetry in the credit market leads to credit rationing. Thus, credit markets across the globe experience some level of credit rationing. A sample of research papers from across the globe showing evidence of credit rationing is reviewed in this section.

In their study, Khan (2022) looks at how small and medium firms that were credit rationed before the COVID-19 pandemic performed during and after the pandemic. The study looks at data on firms from 19 countries across the globe: Europe (e.g., Greece), South America (e.g., El Salvador), Africa (e.g., Niger), and Asia (e.g., Azerbaijan). In each of these continents, a significant portion of firms were reported to be credit-rationed.

In the South African context, Balogun et al. (2016) and Mutezo (2015) investigate credit rationing in the small and medium-sized enterprises (SMEs) sphere. Both studies report that SMEs in South Africa experience credit rationing. In addition, Gurgand et al. (2022) note that credit rationing is evident in the student funding sphere. From the above sample of literature, it is evident that credit rationing is a global phenomenon. Further, it is important in the South African context.

2.4 Economic Significance of Credit Rationing

Due to credit rationing, potentially productive borrowers are unable to access credit or are granted lower credit amounts than they request. Thus, the investment activities of such borrowers are restricted or suppressed altogether. For borrowers receiving lower credit amounts than requested, their investment outcomes and thus their productivity are constrained. Therefore, their contribution to economic growth is never fully realized. On the other hand, the borrowers who are denied credit are unable to invest altogether and therefore cannot contribute to economic growth.

According to Balogun et al. (2016) and Mutezo (2015), the SMEs in South Africa found to be credit rationed can only grow their production as far as their access to credit allows. The benefits of increased production such as employing more people and paying more taxes are thus also

limited. Similarly, in the case of Gurgand et al. (2022), students who are unable to enroll in tertiary institutions due to student credit rationing are unable to grow future earnings at the same rate as those who are granted credit and thus able to enroll (assuming graduation and employment). Thus, credit rationing may contribute to inequality in the economy and limit economic growth.

Moreover, Blinder (1987) argues that monetary policy transmission occurs through credit rationing. Blinder (1987) further shows that credit rationing affects aggregate supply and demand. It is therefore clear that credit rationing is economically important.

2.5 Factors Affecting Credit Rationing

Literature on credit rationing identifies macroeconomic variables such as interest rate, GDP growth rate, borrower net worth, and borrower collateral as some of the key factors that influence the level of credit rationing (Stiglitz & Weiss, 1981; Bernanke, 1992; Everaert *et al*., 2015; Svirydzenka, 2016). Blinder (1987) shows how monetary policy is transmitted through the credit channel by changes in interest rates. Stiglitz and Weiss (1981) motivate the role played by borrower collateral in reducing credit rationing. Everaert *et al*. (2015) estimate the relationship between credit supply, demand, GDP growth rate, and borrower collateral.

2.6 Methods of Measuring Credit Rationing

Credit rationing literature presents two approaches to quantifying credit rationing. The first is a direct approach, which involves conducting surveys among lenders and borrowers to determine the existence and extent of credit rationing. The second is an indirect approach, which involves inferring the existence and level of credit rationing using proxy variables (Calomiris & Longhofer, 2009).

2.6.1 Direct Method Studies

Mutedzo (2015), Balogun et al. (2016) and Gurgand et al. (2022) are examples of studies that use the direct approach to investigate credit rationing since all of them use survey data on firms and individuals in South Africa. Mutedzo (2015) and Gurgand et al. (2022) both measure credit rationing as the proportion of applicants who applied for credit and were rejected. Balogun et al. (2016) use the same definition as Mutedzo (2015) and Gurgand et al. (2022) but include firms that were granted partial credit. A disadvantage of the direct approach is that it can be severely limited since it involves surveys that are time-consuming and labor-intensive.

2.6.2 Indirect Method Studies

Jaffee & Modigliani (1969) and Sealy (1979) are some of the early studies that indirectly measured credit rationing. The proxy used in these studies was the stickiness of commercial lending rates. That is, if open market interest rates keep increasing, the commercial lending rates should follow only up to a point. This proxy was shown to have limitations in characterizing credit rationing by Berger & Udell (1992) since it showed contradictory effects during credit-tight periods.

Laffont & Garcia (1977) explore credit rationing by estimating credit demand and supply functions. In their study, they explore the credit market by assuming that the interest rates are

flexible enough to clear the market (Equilibrium assumption). This is a similar approach considered in *Introductory Econometrics for Finance* (Brooks, 2019), where the equilibrium interest rate is determined against which the actual interest rate can be compared to establish whether credit is rationed.

More recent works building on Laffont and Garcia (1977) include Ghosh & Ghosh (1999), Barajas and Steiner (2002), Poghosyan (2010) and Everaert *et al.* (2015). In this literature, demand is estimated as a function of real interest rate and overall economic activity (given by real GDP growth rate). Credit demand is estimated as a function of real interest rate, overall economic activity (real GDP growth rate), and borrower collateral. The above studies were applied in Europe (Everaert *et al*., 2015), Asia (Ghosh & Ghosh, 1999), South America (Barajas & Steiner, 2002) and Canada (Laffont & Garcia, 1977). There is a visible gap in the literature when it comes to South African indirect studies on credit rationing.

2.7 Theoretical Framework

The theoretical framework of this study is based on the works of Laffont and Garcia (1977), Ghosh and Ghosh (1999), Barajas and Steiner (2002), Everaert *et al*. (2015) and Brooks (2019). In this literature, credit demand is estimated as a function of the real interest rate and the overall economic activity as captured in the GDP growth rate. On the other hand, credit supply is estimated as a function of the real interest rate, borrower wealth, and GDP growth rate.

On the credit demand side, the real interest rate is expected to have a negative coefficient to capture the inverse relationship to credit demand. This is because borrowers are expected to demand less credit when the real interest rates are high since the real interest rate is the cost of borrowing. Moreover, the GDP growth rate is expected to have a positive sign since borrowers are expected to demand more credit during the boom phases of the economic cycle for consumption.

On the credit supply side, the real interest rate is expected to have a positive sign since lenders are expected to supply more credit to capitalize on higher costs of borrowing. Lenders are also expected to be willing to lend funds to borrowers who have wealth that they can use as collateral. Thus, borrower wealth is expected to have a positive sign. Borrower wealth is proxied by the House Price Index (HPI). Furthermore, lenders are expected to increase credit supply during periods of good economic growth. Therefore, the GDP growth rate is expected to have a positive coefficient. Equations 1 and 2 below specify the credit demand and supply functions respectively.

$$CR_{dt} = \gamma_0 + \gamma_1 R_t + \gamma_2 GDP_t + u_t \qquad \textit{Equation 1}$$

$$CR_{st} = \mu_0 + \mu_1 R_t + \mu_2 GDP_t + \mu_3 HPI_t + v_t \qquad \textit{Equation 2}$$

Where: CR_{dt} and CR_{st} are credit demand and supply respectively.

$R_t = Real\ interest\ rate$

$GDP_t = Real\ GDP\ growth\ rate$

$HPI_t = House\ price\ index$ growth rate

$v_t, u_t = Error\ terms$

The empirical technique best suited for estimating this set of equations is the Two Stage Least Squares (2SLS) regression. This is because the interest rate and credit amount are both endogenous. That is, interest rates and credit amounts are dependent on each other and are thus correlated with the error terms (Brooks, 2019). As a result, Ordinary Least Squares cannot be used because the assumption that all input variables are uncorrelated to the error term is violated. Thus, *Equations 1* and *2* must be determined simultaneously. To do so, it is necessary to introduce instrument variables that will be used to remove the endogeneity of the interest rate in *Equations 1* and *2* (Brooks, 2019).

The instrument variables should be correlated to the interest rate, and uncorrelated to the error term. *Introductory Econometrics for Finance* (Brooks, 2019) provides a guide on how to determine appropriate instrument variables. The equilibrium assumption is made to determine the equilibrium interest rate. Under this assumption, *Equations 1* and *2* are manipulated to yield the following reduced-form equation for the equilibrium interest rate (R_t^*):

$$R_t^* = \pi_0 + \pi_1 GDP_t + \pi_2 HPI_t + \varepsilon_t \qquad \textit{Equation 3}$$

Where the π coefficients are combinations of the coefficients from *Equation1* and *2*:

$$\pi_0 = \frac{\mu_0 - \gamma_0}{\gamma_1 - \mu_1}, \quad \pi_1 = \frac{\mu_2 - \gamma_2}{\gamma_1 - \mu_1}, \quad \pi_2 = \frac{\mu_3}{\gamma_1 - \mu_1}, \quad \varepsilon_t = \frac{v_t - u_t}{\gamma_1 - \mu_1}$$

According to Brooks (2019), the right-hand side variables of *Equation 3* can serve as instrument variables for the Two Stage Least Squares regression, along with their lags. Statistical software such as EViews has dedicated Two Stage Least Squares regression packages that handle the estimation of *Equations 1* and *2* given the relevant instrument variables.

Once *Equations 1* and *2* are estimated, the estimated equilibrium interest rate, $\widehat{R_t^*}$, can also be determined from *Equation 3*. To establish credit rationing, the estimated equilibrium interest rate must be compared to the actual interest rate R_t. If it is such that the actual interest rate is statistically less than the equilibrium interest rate, then credit rationing would be shown to exist, as illustrated

in the 'Rationing' scenario in *Figure 2-1*. Equivalently, if the average difference $\overline{(\mathrm{R}_t - \widehat{R_t^*})}$ can be shown to be negative and statistically different from zero, then credit rationing would be shown to be present. Thus, the null hypothesis to test is as follows:

$$H_0: \overline{\mathrm{R}_t - \widehat{R_t^*}} = 0 \qquad \textit{Null Hypothesis}$$

$$H_1: \overline{\mathrm{R}_t - \widehat{R_t^*}} \neq 0 \qquad \textit{Alternative Hypothesis}$$

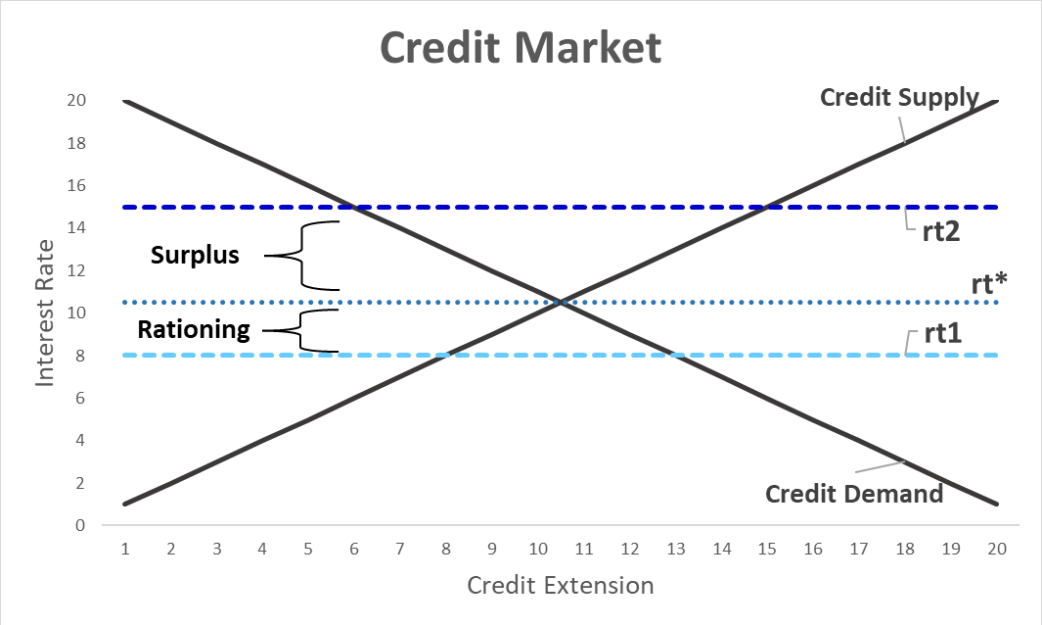

Figure 1: Credit Surplus and Rationing Scenarios in the Credit Market. (Source: Author generated)

If the null hypothesis (see *Null Hypothesis*) cannot be rejected, then credit rationing would be shown to be present. The average level of credit rationing can then be measured as the deviation of the average actual interest rate from the average equilibrium rate:

$$\textit{Average Credit Rationing Level}\ (\%) = \overline{\mathrm{R}_t - \widehat{R_t^*}} \qquad \textit{Equation 4}$$

3 Research Methodology

3.1 Data

The data used in this study was in the form of panel data, comprised of multiple time series for RSA and USA; real interest rates, household credit extension, real and nominal GDP, real house price index, and Rand/Dollar exchange rate. These time series were sourced from the South African Reserve Bank (SARB, 2024), International Monetary Fund (IMF, 2024), and Federal Reserve Bank of St Louis websites (FRED, 2024). The data was sourced in quarterly frequency, except the real interest rates and RSA CPI, which were only available in monthly format. The period used for the data is 2000Q1-2022Q4.

Once the data was sourced, the following steps were taken to prepare it:

i. The monthly time series (real interest rates and RSA CPI) were converted to quarterly data by taking the end-of-period data point per quarter in Microsoft Excel.

ii. RSA credit extension and real GDP were sourced in Rands. They were converted to US Dollars by dividing them by the Rand/Dollar exchange rate.

iii. Moreover, the RSA credit extension was not in real terms. After conversion to US Dollars, it was converted to real credit extension by dividing it by RSA CPI in each period and then multiplying by the CPI value in 2022Q4 to get the amounts in 2022Q4 terms:

$$Real\ CR_{t,RSA} = \frac{Nominal\ CR_{t,RSA}}{CPI_{t,RSA}} * CPI_{2022Q4,RSA} \qquad Equation\ 5$$

iv. The USA credit extension data was deduced from the USA GDP and Credit/GDP ratio by multiplying the two series:

$$Nominal\ c_{t,USA} = (Credit/GDP)_{t,USA} * GDP_{t,USA} \qquad Equation\ 6$$

v. The USA credit extension data was also converted to real credit extension by dividing it by USA CPI:

$$Real\ CR_{t,USA} = \frac{Nominal\ CR_{t,USA}}{CPI_{t,USA}} * CPI_{2022Q4,USA} \qquad Equation\ 7$$

It was important to have the data in real terms so that the effects of inflation were removed. This way, the comparison of values over time is on a like-for-like basis (Brooks, 2019).

3.2 Empirical Analysis

After the data preparation step, the data was imported into EViews for empirical analysis. The following steps were taken during the empirical analysis:

i. The time series were log-transformed except for the real interest rates.
ii. The Phillips-Perron stationarity test was performed for each time series. This test was picked instead of the ADF test because it has the advantages of picking up unit roots close to 1 and automatically determining the number of lags to use in the test (Brooks, 2019).
iii. For non-stationary time series, log differences were taken, and the Phillips-Perron stationarity test was performed on the log-differenced series to ensure stationarity.
iv. Log differences for real GDP and House Price Index were taken regardless of stationarity outcome since the empirical model takes their growth rate as input.
v. Descriptive statistics for each variable were computed.
vi. Two-stage Least Squares regression was performed as outlined in section 2.7.
vii. Residual diagnostics tests (Breusch-Godfrey Serial Correlation LM Test and Breusch-Pagan-Godfrey Heteroskedasticity Test) were performed for the fitted models.
viii. The equilibrium interest rate was calculated and compared with the actual interest rate to test the *Null Hypothesis*.
ix. The average level of credit rationing was computed as per *Equation 4.*

4 Results and Discussion

In this chapter, the results of the empirical analysis are presented along with a discussion. Table 1 below presents details about the variables presented in this chapter.

Table 1: Variable names, units, codes, and descriptions.

VARIABLE	UNITS	CODE	DESCRIPTION
REAL HOUSEHOLD CREDIT LEVEL	$	CR	Credit to households adjusted for inflation (2022Q4 prices)
REAL INTEREST RATE	%	R	The real prime lending rate
REAL GDP	$	GDP	GDP adjusted for inflation (2022Q4 prices)
REAL HOUSE PRICE INDEX	%	HPI	HPI adjusted for inflation (2010=100)
ESTIMATED EQUILIBRIUM REAL INTEREST RATE	%	$\widehat{R^*}$	This real rate clears the credit market, as estimated from the credit supply and demand models.
LOGARITHM OF VARIABLE V	-	LOG(V)	Taking the logarithm of variable V.
THE FIRST DIFFERENCE OF LOGARITHM OF V	-	DLOG(V)	Taking the first difference of the logarithms of variable V
THE SECOND DIFFERENCE OF LOGARITHM OF V	-	DDLOG(V)	Taking the second difference of the logarithms of variable V

4.1 Descriptive Statistics

The descriptive statistics of the input data (levels) below were prepared to better understand the structure of the data. Namely, its distribution in terms of central tendency and dispersion. Looking at Tables 2 and 3, RSA real interest rates were on average higher than USA real interest rates between 2000 and 2022. Moreover, RSA real interest rates varied more about the mean than USA real interest rates, as shown by the standard deviations (1.67% vs 0.87%). As expected, the USA average real GDP far exceeded RSA's average real GDP ($17.60B vs $103.00M), as did credit ($17.80B vs $168.00M). On the other hand, the average House Price Index was higher in the USA than in RSA (121.03% vs 92.97%). This shows that on average US house prices changed faster than RSA house prices since 2010.

Table 2: RSA Descriptive Statistics

	R (%)	CR ($ M)	GDP ($ M)	HPI (%)
MEAN	4,78	168,00	103,00	92,97
MEDIAN	4,94	154,00	100,00	98,53
MAXIMUM	8,58	299,00	150,00	123,54
MINIMUM	0,79	67,2,00	53,50	51,85
STD. DEV.	1,67	57,10	25,50	18,53
OBSERVATIONS	92	92	92	92

Table 3: USA Descriptive Statistics

	R (%)	CR ($ B)	GDP ($ B)	HPI (%)
MEAN	1,08	17,80	17,60	121,03
MEDIAN	0,96	18,20	17,00	118,77
MAXIMUM	3,44	20,60	22,00	161,06
MINIMUM	-0,34	12,20	13,90	93,98
STD. DEV.	0,87	2,18	2,28	19,39
OBSERVATIONS	92	92	92	92

4.2 Stationarity Test Results

Tables 3 and 4 below show the results of the Phillips-Perron stationarity test for the RSA and USA data respectively. As shown in Tables 4 and 5, all levels were found to be non-stationary according to Prob>0.05. Thus, the first differences for all variables were taken and the Phillips-Perron stationary test was redone. As shown, all first difference variables were found to be stationary except for LOG(HPI), which had Prob>0.05 for both RSA and USA. The Phillips-Perron stationary test for the second difference of LOG(HPI) returned Prob=0. Thus, the input variables to use in the Two Stage Least Squares regression are DLOG(CR), DR, DLOG(GDP), and DDLOG(HPI).

Table 4: RSA Phillips-Perron Stationarity Test Results at Level, First and Second Difference.

	LEVEL		**FIRST DIFFERENCE**		**SECOND DIFFERENCE**	
	Adj. t-Stat	Prob	Adj. t-Stat	Prob	Adj. t-Stat	Prob
R	-2,85	0,18	-9,60	0,00	-	-
LOG(CR)	-1,18	0,91	-6,97	0,00	-	-
LOG(GDP)	-1,78	0,71	-8,42	0,00	-	-
LOG(HPI)	-1,31	0,88	-3,11	0,11	-7,90	0,00

Table 5: USA Phillips-Perron Stationarity Test Results at Level, First and Second Difference.

	LEVEL		**FIRST DIFFERENCE**		**SECOND DIFFERENCE**	
	Adj. t-Stat	Prob	Adj. t-Stat	Prob	Adj. t-Stat	Prob
R	-2,46	0,35	-10,63	0,00	-	-
LOG(CR)	-2,3	0,43	-7,82	0,00	-	-
LOG(GDP)	-3,03	0,13	-11,8	0,00	-	-
LOG(HPI)	-1,38	0,86	-2,66	0,25	-10,21	0,00

4.3 Two Stage Least Squares Regression Results

Tables 5 and 6 below present the Two Stage Least Squares regression and Breusch-Godfrey Serial Correlation LM test results for RSA Credit Supply and Demand models. From Table 6, the RSA coefficients of DR for both Credit Supply and Demand are positive (0.0030 and 0.0756 respectively). This is contrary to the expectation that the sign should be negative in the Demand model since the cost of borrowing is inversely proportional to the amount of funds demanded.

Similarly, the USA coefficients of DR for both Credit Supply and Demand are negative (-0,0472 and -0,0778 respectively). The coefficient is expected to be positive in the Supply model since lenders are expected to lend more at higher costs of borrowing. However, DR is shown to be statistically insignificant for both Credit Demand and Supply models in RSA and USA at 95% confidence.

DLOG(GDP) was found to be statistically significant for both Credit Supply and Demand models in both RSA and USA at 95% confidence. Moreover, the signs of the coefficients were positive, as expected since both supply and demand are expected to be directly proportional to GDP growth. Notably, the DLOG(GDP) coefficients are higher for the USA than RSA. Thus, for the same GDP growth, credit supply and demand react more in the USA than in RSA. However, in both countries, credit supply reacts more to GDP growth rates than credit demand. DDLOG(HPI) was found to be statistically insignificant for both Credit Demand and Supply models in both countries. The negative sign in both countries is contrary to the expectation that lenders would supply more credit to borrowers if their wealth (in the form of their house prices) increases.

Table 6: RSA Two Stage Least Squares Regression Results

	CREDIT DEMAND	CREDIT SUPPLY
CONSTANT	0,0047	0,0087
	(0,0044)	(0,0072)
DR	0,0030	0,0756
	(0,0181)	(0,0710)
DLOG(GDP)	0,7857*	0,8653*
	(0,0570)	(0,1111)
DDLOG(HPI)	-	-1,3783
	-	(1,4496)
R-SQUARED	0,7199	0,4013
ADJ. R-SQUARED	0,7135	0,3799
NO OBSERVATIONS	90	88

Standard errors are reported in parentheses.

* Indicates significance at a 95% confidence interval.

Table 7: USA Two Stage Least Squares Regression Results.

	CREDIT DEMAND	CREDIT SUPPLY
CONSTANT	-0,0008	-0,0014
	(0,0022)	(0,0060)
DR	-0,0472	-0,0778
	(0,0280)	(0,2372)
DLOG(GDP)	1,0659*	1,1185*
	(0,1520)	(0,4611)
DDLOG(HPI)	-	-0,1717
	-	(1,3637)
R-SQUARED	-0,0238	-1,1268
ADJ. R-SQUARED	-0,0473	-1,2028
NO OBSERVATIONS	90	88

Standard errors are reported in parentheses.

* Indicates significance at a 95% confidence interval.

Diagnostic tests were performed to ensure that the estimated models were statistically valid. Tables 8 and 9 below present the Breusch-Godfrey Serial Correlation LM test results for both RSA and USA Credit Supply and Demand models. As shown by Prob. Chi-Square (2)>0.05, the null hypothesis (no serial correlation at up to 2 lags) could not be rejected at a 95% confidence. Thus, the estimated models have been shown to have no autocorrelation.

Table 8: RSA Breusch-Godfrey Serial Correlation LM Test Results

NULL HYPOTHESIS: NO SERIAL CORRELATION AT UP TO 2 LAGS		
	Obs*R-squared	Prob. Chi-Square (2)
CREDIT DEMAND	0.7774	0.6780
CREDIT SUPPLY	0.2823	0.8683

Table 9: USA Breusch-Godfrey Serial Correlation LM Test Results

NULL HYPOTHESIS: NO SERIAL CORRELATION AT UP TO 2 LAGS		
	Obs*R-squared	Prob. Chi-Square (2)
CREDIT DEMAND	4.5628	0.1021
CREDIT SUPPLY	0.3214	0.8515

Moreover, Tables 10 and 11 below show the results for the Breusch-Pagan-Godfrey Heteroskedasticity tests for RSA and USA Credit Supply and Demand models respectively. The null hypothesis for these tests is that there is no heteroskedasticity in the models. Based on the probability values Prob. Chi-Square (3) being greater than 0.05 for both RSA and USA models, the is not rejected at a 95% confidence interval. Thus, the models have no heteroskedasticity.

Table 10: RSA Breusch-Pagan-Godfrey Heteroskedasticity Test Results

NULL HYPOTHESIS: NO HETEROSKEDASTICITY		
	Obs*R-squared	Prob. Chi-Square (3)
CREDIT DEMAND	1.2968	0.5229
CREDIT SUPPLY	6.2141	0.1016

Table 11: USA Breusch-Pagan-Godfrey Heteroskedasticity Test Results

NULL HYPOTHESIS: NO HETEROSKEDASTICITY		
	Obs*R-squared	Prob. Chi-Square (3)
CREDIT DEMAND	2.2143	0.3305
CREDIT SUPPLY	1.2320	0.7453

4.4 Credit Rationing Estimation

From the credit supply and demand models presented above, the equilibrium real interest rates were determined as outlined in section 2.7. Figure 2 shows RSA DR and $\widehat{DR}^*$ between 2000 and 2022, while Figure 3 shows the difference between DR and $\widehat{DR}^*$. There are notable periods such as 2003,2008 and 2020-2021 where DR is below $\widehat{DR}^*$, suggesting credit rationing. Similarly, periods such as 2002, 2009-2010, 2014-2015 and 2022 had DR above $\widehat{DR}^*$, suggesting an excess supply of credit. It is evident from Figure 2 that $\widehat{DR}^*$oscillates about 0, mostly confined between -0.5% and 0.5%.

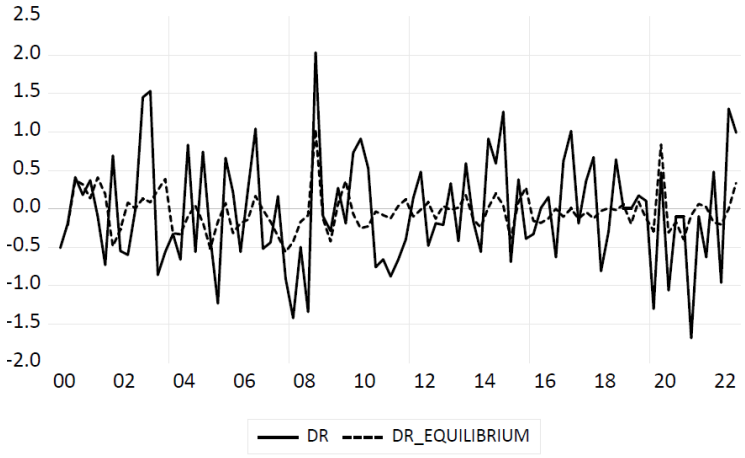

Figure 2: RSA Real Interest Rate and Estimated Equilibrium Real Interest Rate over time (2000-2022).

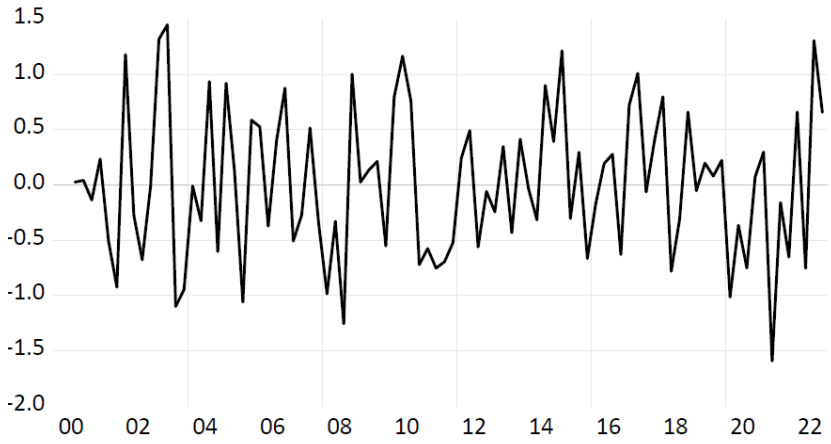

Figure 3: RSA Difference between Real Interest Rate and Estimated Equilibrium Real Interest Rate over time (2000-2022).

Figures 4 and 5 show USA DR and $\widehat{DR}^*$ and their difference respectively. Similar periods of rationing as RSA are observed for the USA, 2002, 2007-2008, and 2022. Similarly, periods such as 2003, 2005, 2016-2017, and 2022 had DR above $\widehat{DR}^*$, suggesting an excess supply of credit. Figure 4 shows that $\widehat{DR}^*$oscillated close about 0 quite closely, mostly confined between -0.3% and 0.3%.

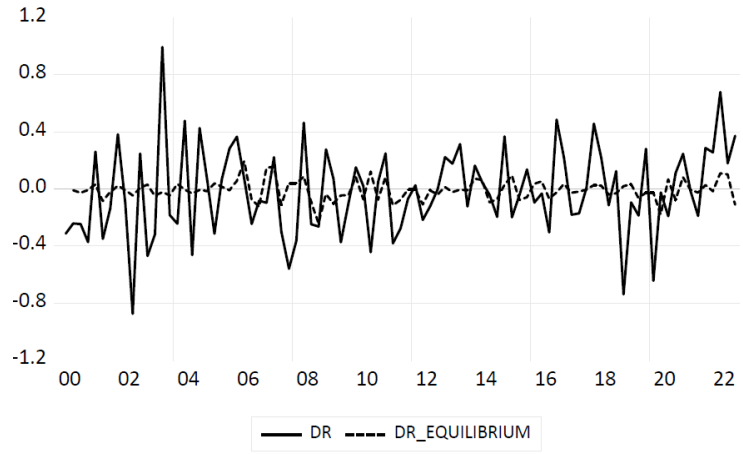

Figure 4: USA Real Interest Rate and Equilibrium Real Interest Rate Plot over time (2000-2022)

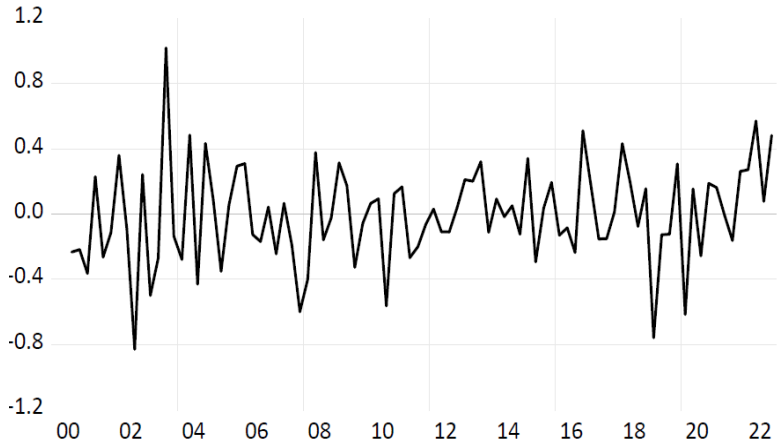

Figure 5: USA Plot of Difference between Real Interest and Equilibrium Interest over time (2000-2022)

To complement Figures 2-5, Tables 12 and 13 present the summary statistics for DR, $\widehat{DR}^*$ and $DR - \widehat{DR}^*$ for RSA and USA respectively. Judging by the means, $DR > \widehat{DR}^*$ for RSA while, $DR < \widehat{DR}^*$ for USA. That is, on average RSA credit was supplied in excess, while USA credit was rationed.

With the averages given, the level of credit rationing can be calculated according to *Equation 4.* For RSA that would be 0.0075%, meaning a 0.0075% excess. For the USA the level of rationing would be -0.0081%, representing a 0.0081% credit rationing. However, the statistical significance of these credit rationing figures still needs to be determined.

Table 12: RSA summary statistics for Real Interest Rate, Estimated Equilibrium Interest Rate, and their difference.

	DR	$\widehat{DR^*}$	$DR - \widehat{DR^*}$
MEAN	-0.0339	-0.0414	0.0075
MEDIAN	-0.1000	-0.0552	-0.0111
MAXIMUM	2.0300	1.0295	1.4475
MINIMUM	-1.6800	-0.5618	-1.5925
STD. DEV.	0.7174	0.2543	0.6695
OBSERVATIONS	90	90	90

Table 13: USA summary statistics of Real Interest Rate, Estimated Equilibrium Interest Rate, and their difference.

	DR	$\widehat{DR^*}$	$DR - \widehat{DR^*}$
MEAN	-0.0172	-0.0092	-0.0081
MEDIAN	-0.038	-0.0106	-0.0132
MAXIMUM	0.9921	0.1929	1.0159
MINIMUM	-0.8738	-0.2412	-0.8282
STD. DEV.	0.3136	0.0710	0.3052
OBSERVATIONS	90	90	90

Table 14 presents the results for testing the *Null Hypothesis*. For both RSA and USA, the null hypothesis that there is no credit rationing could not be rejected since probability > 0.05. Thus, while the average differences $DR - \widehat{DR^*}$ for both RSA and USA were shown to be non-zero above, Table 12 shows that they are not statistically different from 0.

Table 14: RSA and USA Credit Rationing Null Hypothesis Test Results.

	$\overline{DR_t - \widehat{DR_t^*}}$	HYPOTHESIZED MEAN	T-STATISTIC	PROBABILITY	CONCLUSION
RSA	0.0075	0.0000	0.1068	0.9152	Fail to reject the Null Hypothesis
USA	-0.0081	0.0000	-0.2509	0.8025	Fail to reject the Null Hypothesis

Null hypothesis: $\overline{DR_t - \widehat{DR_t^*}} = 0$

5 Discussion and Conclusion

Credit Supply and Demand models for RSA and USA were estimated. Among the input variables considered, only the GDP growth rate was found to be statistically significant in explaining credit supply and demand. This finding is contrary to the broader literature on credit market dynamics. For instance, Msomi (2023) and Adão et al. (2022) show that interest rates are key drivers in the credit market. In addition, Daley et al. (2020) show that house prices are key determinants of credit supply.

Using the estimated models, the equilibrium interest rates for RSA and USA were computed. The difference between the actual interest rate and the equilibrium interest rate was also determined. The null hypothesis that the difference between equilibrium and actual interest rates is equal to zero was tested. For both RSA and USA, the null hypothesis could not be rejected. Therefore, credit rationing could not be shown to have existed over the period of observation.

These findings are contrary to the literature since credit markets are expected to exist in a state of disequilibrium, as established by Stiglitz & Weis (1981), and more recently Medhi et al. (2020) and Ying (2022). The discrepancies between the findings of this study and the broader literature were noted. Possible explanation for the discrepancies may be due to the usage of the Two Stage Least Squares regression method for estimating the supply and demand models. This point is elaborated upon in chapter 6 under future work and recommendations.

In conclusion, firstly, only real GDP growth rate was found to be a significant driver of credit supply and demand, while credit rationing could not be shown to be present in the RSA and USA credit markets in the period of observation. Secondly, the findings of this study were shown to disagree with the broader literature.

6 Recommendations and Future Work

More sophisticated regression techniques such as Switching regression can be used to better capture the dynamics between the demand and supply of credit. Unlike Two Stage Least Squares regression, switching regression has the advantage that it does not take the actual credit extension as both credit demand and supply. Rather, it assumes that supply and demand occur in turn to jointly drive credit extension. Thus, it can better estimate supply and demand by partitioning the period of observation between supply regimes and demand regions. Moreover, more input variables can be tested and included to improve the models. While this study looked at RSA and the USA, more countries can be added to further paint an international picture of credit rationing.

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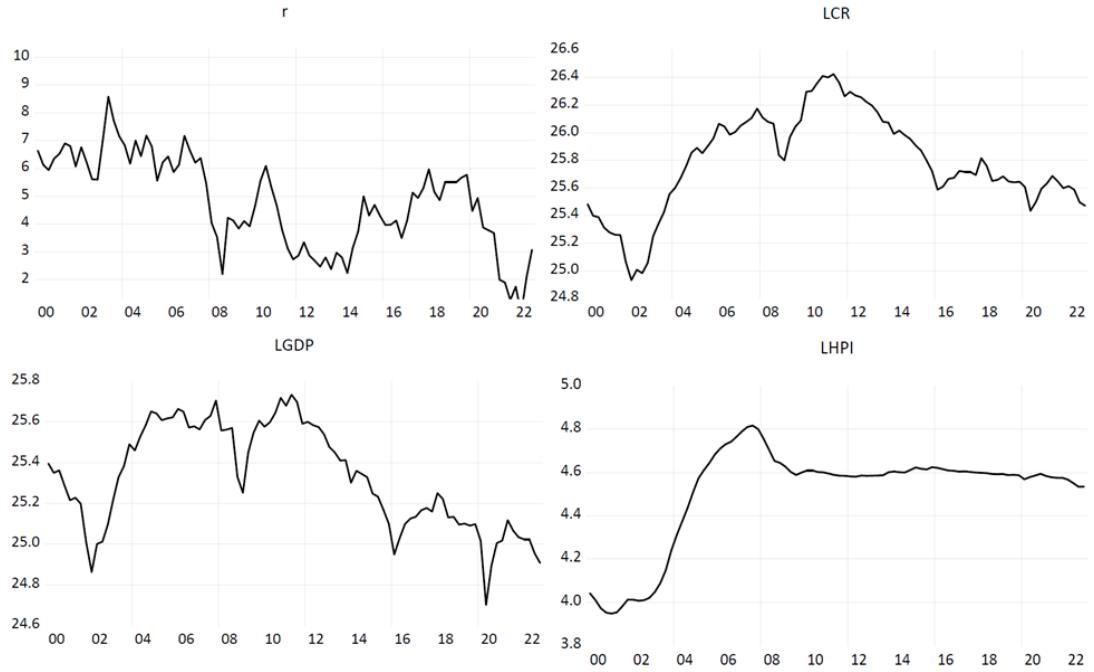
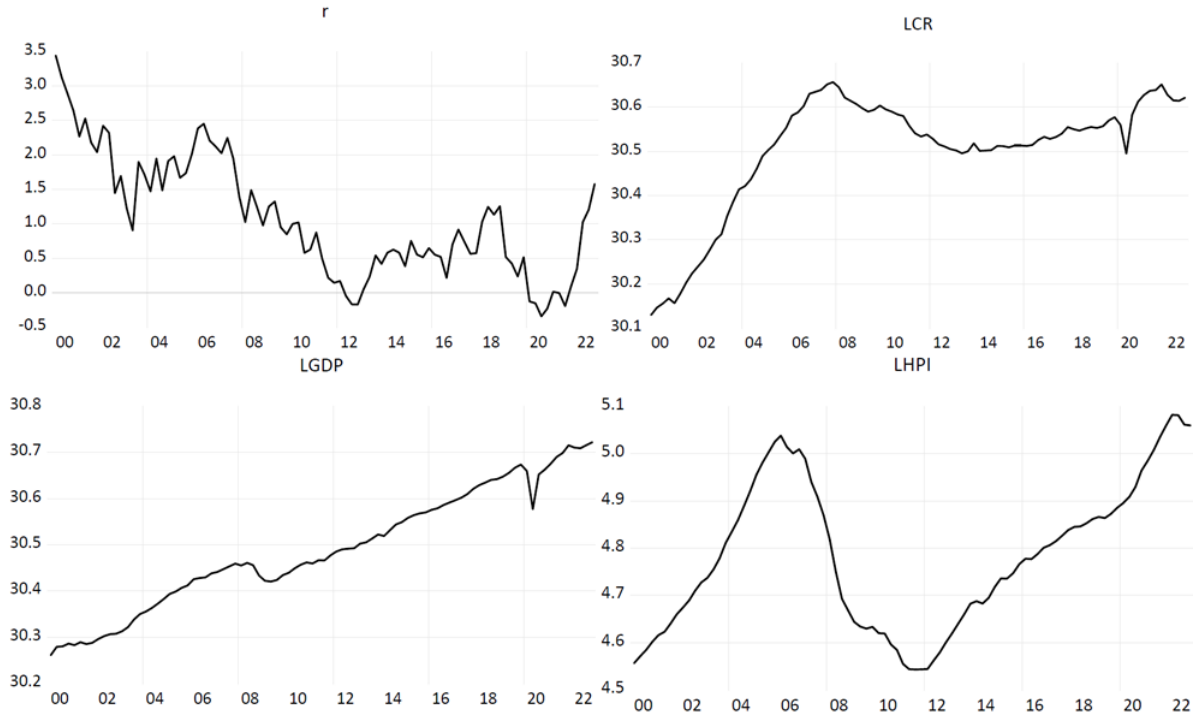
8 APPENDIX

8.1 RSA Input Variable Plots



8.2 USA Input Variable Plots



8.3 RSA Stationarity Test EViews Output

Null Hypothesis: LCR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.177405	0.9088
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.005532
HAC corrected variance (Bartlett kernel)	0.010051

Phillips-Perron Test Equation
Dependent Variable: D(LCR)
Method: Least Squares
Date: 05/15/24 Time: 15:34
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCR(-1)	-0.017172	0.022932	-0.748825	0.4560
C	0.461643	0.589054	0.783703	0.4353
@TREND("3/01/2000")	-0.000411	0.000307	-1.338969	0.1840

R-squared	0.030968	Mean dependent var	-0.000126
Adjusted R-squared	0.008945	S.D. dependent var	0.075973
S.E. of regression	0.075632	Akaike info criterion	-2.293460
Sum squared resid	0.503379	Schwarz criterion	-2.210685
Log likelihood	107.3524	Hannan-Quinn criter.	-2.260065
F-statistic	1.406159	Durbin-Watson stat	1.357988
Prob(F-statistic)	0.250535		

Null Hypothesis: D(LCR) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-6.965899	0.0000
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.004985
HAC corrected variance (Bartlett kernel)	0.005246

Phillips-Perron Test Equation
Dependent Variable: D(LCR,2)
Method: Least Squares
Date: 05/15/24 Time: 15:35
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LCR(-1))	-0.697376	0.100891	-6.912151	0.0000
C	0.019164	0.015664	1.223404	0.2245
@TREND("3/01/2000")	-0.000395	0.000295	-1.341037	0.1834

R-squared	0.354866	Mean dependent var	0.000680
Adjusted R-squared	0.340036	S.D. dependent var	0.088393
S.E. of regression	0.071808	Akaike info criterion	-2.396863
Sum squared resid	0.448612	Schwarz criterion	-2.313536
Log likelihood	110.8588	Hannan-Quinn criter.	-2.363260
F-statistic	23.92788	Durbin-Watson stat	1.986260
Prob(F-statistic)	0.000000		

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.854258	0.1824
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.465233
HAC corrected variance (Bartlett kernel)	0.498798

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 05/15/24 Time: 15:36
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.160353	0.057922	-2.768451	0.0069
C	1.031060	0.415264	2.482903	0.0149
@TREND("3/01/2000")	-0.006538	0.003666	-1.783236	0.0780

R-squared	0.080134	Mean dependent var	-0.039121
Adjusted R-squared	0.059228	S.D. dependent var	0.715109
S.E. of regression	0.693609	Akaike info criterion	2.138594
Sum squared resid	42.33621	Schwarz criterion	2.221370
Log likelihood	-94.30604	Hannan-Quinn criter.	2.171989
F-statistic	3.833061	Durbin-Watson stat	1.898922
Prob(F-statistic)	0.025344		

Null Hypothesis: D(R) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-9.599982	0.0000
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.508119
HAC corrected variance (Bartlett kernel)	0.506454

Phillips-Perron Test Equation
Dependent Variable: D(R,2)
Method: Least Squares
Date: 05/15/24 Time: 15:36
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(R(-1))	-1.038375	0.108165	-9.599922	0.0000
C	-0.023918	0.156705	-0.152633	0.8790
@TREND("3/01/2000")	-0.000256	0.002943	-0.087048	0.9308

R-squared	0.514451	Mean dependent var	0.016667
Adjusted R-squared	0.503289	S.D. dependent var	1.028709
S.E. of regression	0.725011	Akaike info criterion	2.227505
Sum squared resid	45.73073	Schwarz criterion	2.310832
Log likelihood	-97.23770	Hannan-Quinn criter.	2.261107
F-statistic	46.08936	Durbin-Watson stat	1.979962
Prob(F-statistic)	0.000000		

Null Hypothesis: LGDP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.776012	0.7084
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.006353
HAC corrected variance (Bartlett kernel)	0.007160

Phillips-Perron Test Equation
Dependent Variable: D(LGDP)
Method: Least Squares
Date: 05/15/24 Time: 15:37
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP(-1)	-0.064050	0.038422	-1.667014	0.0991
C	1.641957	0.981238	1.673353	0.0978
@TREND("3/01/2000")	-0.000540	0.000365	-1.478084	0.1430

R-squared	0.037312	Mean dependent var	-0.005358
Adjusted R-squared	0.015433	S.D. dependent var	0.081684
S.E. of regression	0.081051	Akaike info criterion	-2.155054
Sum squared resid	0.578102	Schwarz criterion	-2.072278
Log likelihood	101.0549	Hannan-Quinn criter.	-2.121659
F-statistic	1.705353	Durbin-Watson stat	1.729559
Prob(F-statistic)	0.187658		

Null Hypothesis: D(LGDP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 0 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-8.418248	0.0000
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.006524
HAC corrected variance (Bartlett kernel)	0.006524

Phillips-Perron Test Equation
Dependent Variable: D(LGDP,2)
Method: Least Squares
Date: 05/15/24 Time: 15:38
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LGDP(-1))	-0.896243	0.106464	-8.418248	0.0000
C	0.008222	0.017766	0.462764	0.6447
@TREND("3/01/2000")	-0.000272	0.000334	-0.812257	0.4189

R-squared	0.449021	Mean dependent var	-1.55E-05
Adjusted R-squared	0.436354	S.D. dependent var	0.109424
S.E. of regression	0.082151	Akaike info criterion	-2.127741
Sum squared resid	0.587150	Schwarz criterion	-2.044414
Log likelihood	98.74834	Hannan-Quinn criter.	-2.094138
F-statistic	35.45032	Durbin-Watson stat	1.973897
Prob(F-statistic)	0.000000		

Null Hypothesis: LHPI has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.309907	0.8792
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000548
HAC corrected variance (Bartlett kernel)	0.002428

Phillips-Perron Test Equation
Dependent Variable: D(LHPI)
Method: Least Squares
Date: 05/15/24 Time: 15:39
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LHPI(-1)	-0.009856	0.013040	-0.755832	0.4518
C	0.062286	0.055890	1.114438	0.2681
@TREND("3/01/2000")	-0.000271	0.000117	-2.320073	0.0227

R-squared	0.120384	Mean dependent var	0.005413
Adjusted R-squared	0.100393	S.D. dependent var	0.025098
S.E. of regression	0.023804	Akaike info criterion	-4.605481
Sum squared resid	0.049865	Schwarz criterion	-4.522705
Log likelihood	212.5494	Hannan-Quinn criter.	-4.572086
F-statistic	6.021835	Durbin-Watson stat	0.271269
Prob(F-statistic)	0.003539		

Null Hypothesis: D(LHPI) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.106717	0.1111
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000136
HAC corrected variance (Bartlett kernel)	0.000148

Phillips-Perron Test Equation
Dependent Variable: D(LHPI,2)
Method: Least Squares
Date: 05/15/24 Time: 15:39
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHPI(-1))	-0.160985	0.053066	-3.033660	0.0032
C	0.005109	0.002793	1.829111	0.0708
@TREND("3/01/2000")	-8.36E-05	5.13E-05	-1.630291	0.1067

R-squared	0.099441	Mean dependent var	0.000344
Adjusted R-squared	0.078738	S.D. dependent var	0.012374
S.E. of regression	0.011877	Akaike info criterion	-5.995627
Sum squared resid	0.012273	Schwarz criterion	-5.912300
Log likelihood	272.8032	Hannan-Quinn criter.	-5.962024
F-statistic	4.803320	Durbin-Watson stat	1.615645
Prob(F-statistic)	0.010502		

Null Hypothesis: D(LHPI,2) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-7.899993	0.0000
Test critical values:	1% level	-4.064453	
	5% level	-3.461094	
	10% level	-3.156776	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000149
HAC corrected variance (Bartlett kernel)	9.95E-05

Phillips-Perron Test Equation
Dependent Variable: D(LHPI,3)
Method: Least Squares
Date: 05/15/24 Time: 15:40
Sample (adjusted): 12/01/2000 12/01/2022
Included observations: 89 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHPI(-1),2)	-0.866519	0.107977	-8.025014	0.0000
C	0.001915	0.002753	0.695452	0.4886
@TREND("3/01/2000")	-3.19E-05	5.14E-05	-0.620352	0.5367

R-squared	0.428266	Mean dependent var	0.000286
Adjusted R-squared	0.414970	S.D. dependent var	0.016223
S.E. of regression	0.012408	Akaike info criterion	-5.907760
Sum squared resid	0.013241	Schwarz criterion	-5.823873
Log likelihood	265.8953	Hannan-Quinn criter.	-5.873948
F-statistic	32.20986	Durbin-Watson stat	1.871899
Prob(F-statistic)	0.000000		

8.4 USA Stationarity Test EViews Output

Null Hypothesis: LCR has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.304765	0.4269
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000263
HAC corrected variance (Bartlett kernel)	0.000347

Phillips-Perron Test Equation
Dependent Variable: D(LCR)
Method: Least Squares
Date: 05/15/24 Time: 15:17
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LCR(-1)	-0.040543	0.016844	-2.406941	0.0182
C	1.244560	0.511265	2.434277	0.0169
@TREND("3/01/2000")	-5.46E-05	8.58E-05	-0.636991	0.5258

R-squared	0.136254	Mean dependent var	0.005396
Adjusted R-squared	0.116623	S.D. dependent var	0.017544
S.E. of regression	0.016489	Akaike info criterion	-5.339817
Sum squared resid	0.023927	Schwarz criterion	-5.257041
Log likelihood	245.9617	Hannan-Quinn criter.	-5.306422
F-statistic	6.940877	Durbin-Watson stat	1.682806
Prob(F-statistic)	0.001589		

Null Hypothesis: D(LCR) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 3 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-7.823562	0.0000
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000274
HAC corrected variance (Bartlett kernel)	0.000287

Phillips-Perron Test Equation
Dependent Variable: D(LCR,2)
Method: Least Squares
Date: 05/15/24 Time: 15:18
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LCR(-1))	-0.823251	0.105724	-7.786828	0.0000
C	0.011327	0.003948	2.869142	0.0052
@TREND("3/01/2000")	-0.000151	7.14E-05	-2.110687	0.0377

R-squared	0.410784	Mean dependent var	-0.000108
Adjusted R-squared	0.397239	S.D. dependent var	0.021703
S.E. of regression	0.016850	Akaike info criterion	-5.296212
Sum squared resid	0.024700	Schwarz criterion	-5.212885
Log likelihood	241.3296	Hannan-Quinn criter.	-5.262610
F-statistic	30.32691	Durbin-Watson stat	2.004569
Prob(F-statistic)	0.000000		

Null Hypothesis: R has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 4 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.455994	0.3490
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.088200
HAC corrected variance (Bartlett kernel)	0.089406

Phillips-Perron Test Equation
Dependent Variable: D(R)
Method: Least Squares
Date: 05/15/24 Time: 15:20
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
R(-1)	-0.147922	0.060734	-2.435570	0.0169
C	0.222073	0.152963	1.451805	0.1501
@TREND("3/01/2000")	-0.001805	0.002001	-0.901700	0.3697

R-squared	0.092128	Mean dependent var	-0.020486
Adjusted R-squared	0.071495	S.D. dependent var	0.313416
S.E. of regression	0.302004	Akaike info criterion	0.475660
Sum squared resid	8.026181	Schwarz criterion	0.558436
Log likelihood	-18.64255	Hannan-Quinn criter.	0.509055
F-statistic	4.464984	Durbin-Watson stat	2.054392
Prob(F-statistic)	0.014226		

Null Hypothesis: D(R) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-10.63258	0.0000
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.093273
HAC corrected variance (Bartlett kernel)	0.081943

Phillips-Perron Test Equation
Dependent Variable: D(R,2)
Method: Least Squares
Date: 05/15/24 Time: 15:21
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(R(-1))	-1.124626	0.106707	-10.53938	0.0000
C	-0.121273	0.068179	-1.778751	0.0788
@TREND("3/01/2000")	0.002171	0.001276	1.701210	0.0925

R-squared	0.560788	Mean dependent var	0.007604
Adjusted R-squared	0.550691	S.D. dependent var	0.463413
S.E. of regression	0.310628	Akaike info criterion	0.532323
Sum squared resid	8.394600	Schwarz criterion	0.615650
Log likelihood	-20.95452	Hannan-Quinn criter.	0.565925
F-statistic	55.54101	Durbin-Watson stat	2.030782
Prob(F-statistic)	0.000000		

Null Hypothesis: LGDP has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-3.025921	0.1310
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000158
HAC corrected variance (Bartlett kernel)	0.000145

Phillips-Perron Test Equation
Dependent Variable: D(LGDP)
Method: Least Squares
Date: 05/15/24 Time: 15:23
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LGDP(-1)	-0.201432	0.064290	-3.133160	0.0023
C	6.102068	1.945986	3.135719	0.0023
@TREND("3/01/2000")	0.000962	0.000311	3.095736	0.0026

R-squared	0.100367	Mean dependent var	0.005058
Adjusted R-squared	0.079920	S.D. dependent var	0.013306
S.E. of regression	0.012763	Akaike info criterion	-5.852095
Sum squared resid	0.014335	Schwarz criterion	-5.769319
Log likelihood	269.2703	Hannan-Quinn criter.	-5.818700
F-statistic	4.908808	Durbin-Watson stat	2.152138
Prob(F-statistic)	0.009525		

Null Hypothesis: D(LGDP) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 5 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-11.79887	0.0000
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000168
HAC corrected variance (Bartlett kernel)	0.000129

Phillips-Perron Test Equation
Dependent Variable: D(LGDP,2)
Method: Least Squares
Date: 05/15/24 Time: 15:23
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LGDP(-1))	-1.193624	0.104574	-11.41412	0.0000
C	0.005357	0.002901	1.847029	0.0681
@TREND("3/01/2000")	1.15E-05	5.36E-05	0.213933	0.8311

R-squared	0.599672	Mean dependent var	-0.000130
Adjusted R-squared	0.590469	S.D. dependent var	0.020627
S.E. of regression	0.013200	Akaike info criterion	-5.784455
Sum squared resid	0.015159	Schwarz criterion	-5.701128
Log likelihood	263.3005	Hannan-Quinn criter.	-5.750853
F-statistic	65.16095	Durbin-Watson stat	2.034461
Prob(F-statistic)	0.000000		

Null Hypothesis: LHPI has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 6 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-1.381228	0.8601
Test critical values:	1% level	-4.062040	
	5% level	-3.459950	
	10% level	-3.156109	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000422
HAC corrected variance (Bartlett kernel)	0.002097

Phillips-Perron Test Equation
Dependent Variable: D(LHPI)
Method: Least Squares
Date: 05/15/24 Time: 15:24
Sample (adjusted): 6/01/2000 12/01/2022
Included observations: 91 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LHPI(-1)	-0.006025	0.015093	-0.399160	0.6907
C	0.032103	0.070843	0.453153	0.6516
@TREND("3/01/2000")	4.84E-05	8.91E-05	0.542693	0.5887

R-squared	0.003891	Mean dependent var	0.005527
Adjusted R-squared	-0.018748	S.D. dependent var	0.020702
S.E. of regression	0.020895	Akaike info criterion	-4.866232
Sum squared resid	0.038420	Schwarz criterion	-4.783456
Log likelihood	224.4135	Hannan-Quinn criter.	-4.832837
F-statistic	0.171861	Durbin-Watson stat	0.328928
Prob(F-statistic)	0.842378		

Null Hypothesis: D(LHPI) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 2 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-2.664842	0.2536
Test critical values:	1% level	-4.063233	
	5% level	-3.460516	
	10% level	-3.156439	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000129
HAC corrected variance (Bartlett kernel)	0.000114

Phillips-Perron Test Equation
Dependent Variable: D(LHPI,2)
Method: Least Squares
Date: 05/15/24 Time: 15:27
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHPI(-1))	-0.166001	0.059049	-2.811257	0.0061
C	0.000348	0.002510	0.138677	0.8900
@TREND("3/01/2000")	8.58E-06	4.70E-05	0.182379	0.8557

R-squared	0.083286	Mean dependent var	-0.000184
Adjusted R-squared	0.062212	S.D. dependent var	0.011950
S.E. of regression	0.011572	Akaike info criterion	-6.047658
Sum squared resid	0.011651	Schwarz criterion	-5.964331
Log likelihood	275.1446	Hannan-Quinn criter.	-6.014055
F-statistic	3.952113	Durbin-Watson stat	1.979021
Prob(F-statistic)	0.022760		

Null Hypothesis: D(LHPI,2) has a unit root
Exogenous: Constant, Linear Trend
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

		Adj. t-Stat	Prob.*
Phillips-Perron test statistic		-10.20716	0.0000
Test critical values:	1% level	-4.064453	
	5% level	-3.461094	
	10% level	-3.156776	

*MacKinnon (1996) one-sided p-values.

Residual variance (no correction)	0.000142
HAC corrected variance (Bartlett kernel)	9.76E-05

Phillips-Perron Test Equation
Dependent Variable: D(LHPI,3)
Method: Least Squares
Date: 05/15/24 Time: 15:26
Sample (adjusted): 12/01/2000 12/01/2022
Included observations: 89 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LHPI(-1),2)	-1.084577	0.108963	-9.953592	0.0000
C	-0.000189	0.002677	-0.070641	0.9438
@TREND("3/01/2000")	-3.28E-07	5.00E-05	-0.006565	0.9948

R-squared	0.535496	Mean dependent var	0.000219
Adjusted R-squared	0.524694	S.D. dependent var	0.017571
S.E. of regression	0.012114	Akaike info criterion	-5.955857
Sum squared resid	0.012619	Schwarz criterion	-5.871971
Log likelihood	268.0356	Hannan-Quinn criter.	-5.922045
F-statistic	49.57195	Durbin-Watson stat	2.022404
Prob(F-statistic)	0.000000		

8.5 RSA Two Stage Least Squares EViews Output

Dependent Variable: DLCR
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:48
Sample (adjusted): 3/01/2001 12/01/2022
Included observations: 88 after adjustments
DLCR = C(1) + C(2)*DR + C(3)*DLGDP + C(4)*DDLHPI
Instrument specification: DLGDP DDLHPI DDLHPI(-1) DDLHPI(-2)
Constant added to instrument list

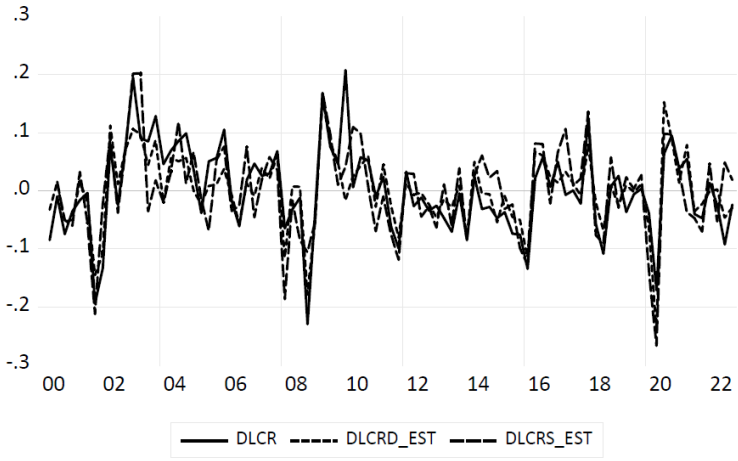
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.008651	0.007205	1.200660	0.2333
C(2)	0.075621	0.070570	1.071577	0.2870
C(3)	0.865298	0.111110	7.787771	0.0000
C(4)	-1.378304	1.449564	-0.950841	0.3444

R-squared	0.401288	Mean dependent var	0.001794
Adjusted R-squared	0.379906	S.D. dependent var	0.076286
S.E. of regression	0.060072	Sum squared resid	0.303126
Durbin-Watson stat	2.056958	J-statistic	0.581766
Instrument rank	5	Prob(J-statistic)	0.445621

Dependent Variable: DLCR
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:16
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments
DLCR = C(1) + C(2)*DR + C(3)*DLGDP
Instrument specification: DLGDP DDLHPI
Constant added to instrument list

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.004777	0.004349	1.098445	0.2750
C(2)	0.002982	0.018139	0.164412	0.8698
C(3)	0.785696	0.056968	13.79188	0.0000

R-squared	0.719887	Mean dependent var	0.000817
Adjusted R-squared	0.713447	S.D. dependent var	0.075861
S.E. of regression	0.040609	Sum squared resid	0.143469
Durbin-Watson stat	1.957508	J-statistic	5.48E-29
Instrument rank	3		



8.6 USA Two Stage Least Squares EViews Output

Dependent Variable: DLCR
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:44
Sample (adjusted): 3/01/2001 12/01/2022
Included observations: 88 after adjustments
DLCR = C(1) + C(2)*DR + C(3)*DLGDP + C(4)*DDLHPI
Instrument specification: DLGDP DDLHPI DDLHPI(-1) DDLHPI(-2)
Constant added to instrument list

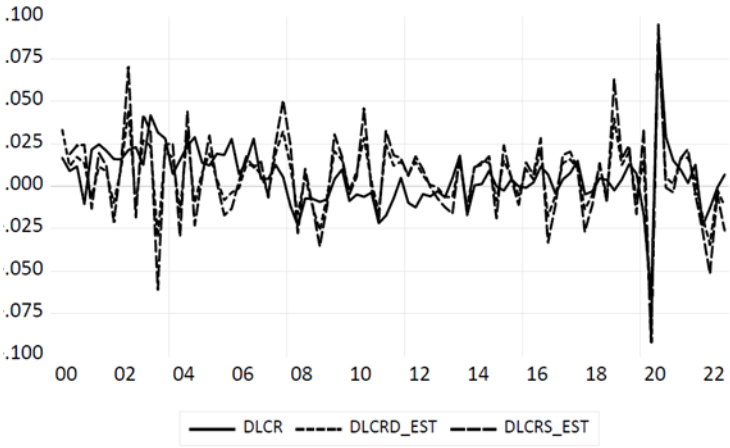
	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.001351	0.005987	-0.225601	0.8221
C(2)	-0.077799	0.237170	-0.328030	0.7437
C(3)	1.118460	0.461090	2.425685	0.0174
C(4)	-0.171681	1.363737	-0.125890	0.9001

R-squared	-1.126816	Mean dependent var	0.005158
Adjusted R-squared	-1.202774	S.D. dependent var	0.017785
S.E. of regression	0.026396	Sum squared resid	0.058529
Durbin-Watson stat	2.009488	J-statistic	0.266116
Instrument rank	5	Prob(J-statistic)	0.605949

Dependent Variable: DLCR
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:31
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments
DLCR = C(1) + C(2)*DR + C(3)*DLGDP
Instrument specification: DLGDP DDLHPI
Constant added to instrument list

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.000781	0.002153	-0.362709	0.7177
C(2)	-0.047243	0.027999	-1.687329	0.0951
C(3)	1.065935	0.152023	7.011661	0.0000

R-squared	-0.023787	Mean dependent var	0.005271
Adjusted R-squared	-0.047323	S.D. dependent var	0.017602
S.E. of regression	0.018013	Sum squared resid	0.028230
Durbin-Watson stat	1.695339	J-statistic	1.91E-27
Instrument rank	3		



8.7 RSA Breusch-Godfrey Serial Correlation LM EViews Output

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

Obs*R-squared	0.282334	Prob. Chi-Square(2)	0.8683

Test Equation:
Dependent Variable: RESID
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:48
Sample: 3/01/2001 12/01/2022
Included observations: 88
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000184	0.007289	0.025288	0.9799
C(2)	0.001104	0.071459	0.015444	0.9877
C(3)	0.001729	0.112481	0.015368	0.9878
C(4)	-0.069274	1.471380	-0.047081	0.9626
RESID(-1)	-0.035596	0.111594	-0.318978	0.7506
RESID(-2)	-0.049119	0.117234	-0.418978	0.6763

R-squared	0.003208	Mean dependent var	5.91E-18
Adjusted R-squared	-0.057572	S.D. dependent var	0.059027
S.E. of regression	0.060703	Akaike info criterion	-2.699917
Sum squared resid	0.302153	Schwarz criterion	-2.531007
Log likelihood	124.7963	Hannan-Quinn criter.	-2.631867
F-statistic	0.052786	Durbin-Watson stat	1.987710
Prob(F-statistic)	0.998197		

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

Obs*R-squared	0.777363	Prob. Chi-Square(2)	0.6780

Test Equation:
Dependent Variable: RESID
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:28
Sample: 9/01/2000 12/01/2022
Included observations: 90
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2.76E-05	0.004381	0.006291	0.9950
C(2)	0.002507	0.018576	0.134982	0.8929
C(3)	-0.003365	0.058127	-0.057887	0.9540
RESID(-1)	0.021891	0.111446	0.196428	0.8447
RESID(-2)	0.092716	0.110285	0.840697	0.4029

R-squared	0.008637	Mean dependent var	2.27E-18
Adjusted R-squared	-0.038015	S.D. dependent var	0.040150
S.E. of regression	0.040906	Akaike info criterion	-3.501136
Sum squared resid	0.142229	Schwarz criterion	-3.362257
Log likelihood	162.5511	Hannan-Quinn criter.	-3.445132
F-statistic	0.185143	Durbin-Watson stat	2.006146
Prob(F-statistic)	0.945540		

8.8 USA Breusch-Godfrey Serial Correlation LM EViews Output

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

Obs*R-squared	0.321422	Prob. Chi-Square(2)	0.8515

Test Equation:
Dependent Variable: RESID
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:44
Sample: 3/01/2001 12/01/2022
Included observations: 88
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.000136	0.006057	0.022416	0.9822
C(2)	0.012291	0.240656	0.051075	0.9594
C(3)	0.008161	0.467014	0.017474	0.9861
C(4)	0.067472	1.383407	0.048772	0.9612
RESID(-1)	-0.027435	0.115373	-0.237793	0.8126
RESID(-2)	0.056197	0.113223	0.496344	0.6210

R-squared	0.003653	Mean dependent var	6.31E-19
Adjusted R-squared	-0.057100	S.D. dependent var	0.025937
S.E. of regression	0.026668	Akaike info criterion	-4.344992
Sum squared resid	0.058315	Schwarz criterion	-4.176083
Log likelihood	197.1797	Hannan-Quinn criter.	-4.276943
F-statistic	0.060121	Durbin-Watson stat	1.983584
Prob(F-statistic)	0.997538		

Breusch-Godfrey Serial Correlation LM Test:
Null hypothesis: No serial correlation at up to 2 lags

Obs*R-squared	4.562771	Prob. Chi-Square(2)	0.1021

Test Equation:
Dependent Variable: RESID
Method: Two-Stage Least Squares
Date: 05/18/24 Time: 02:31
Sample: 9/01/2000 12/01/2022
Included observations: 90
Presample missing value lagged residuals set to zero.

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-4.02E-05	0.002129	-0.018860	0.9850
C(2)	-0.007328	0.027856	-0.263068	0.7931
C(3)	-0.004507	0.154991	-0.029081	0.9769
RESID(-1)	0.129700	0.112384	1.154077	0.2517
RESID(-2)	0.170257	0.108964	1.562506	0.1219

R-squared	0.050697	Mean dependent var	-5.31E-17
Adjusted R-squared	0.006024	S.D. dependent var	0.017810
S.E. of regression	0.017756	Akaike info criterion	-5.170217
Sum squared resid	0.026799	Schwarz criterion	-5.031339
Log likelihood	237.6598	Hannan-Quinn criter.	-5.114213
F-statistic	1.134855	Durbin-Watson stat	2.067734
Prob(F-statistic)	0.345659		

8.9 RSA Breusch-Pagan-Godfrey Heteroskedasticity Test EViews Output

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

F-statistic	2.127429	Prob. F(3,84)	0.1028
Obs*R-squared	6.214065	Prob. Chi-Square(3)	0.1016
Scaled explained SS	6.493640	Prob. Chi-Square(3)	0.0899

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/31/24 Time: 22:18
Sample: 3/01/2001 12/01/2022
Included observations: 88

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003429	0.000551	6.223998	0.0000
DR	0.001055	0.000815	1.293861	0.1993
DL_GDP	-0.011235	0.006745	-1.665575	0.0995
DDL_HPI	0.028325	0.047372	0.597935	0.5515

R-squared	0.070614	Mean dependent var	0.003445
Adjusted R-squared	0.037422	S.D. dependent var	0.005247
S.E. of regression	0.005148	Akaike info criterion	-7.656138
Sum squared resid	0.002226	Schwarz criterion	-7.543532
Log likelihood	340.8701	Hannan-Quinn criter.	-7.610772
F-statistic	2.127429	Durbin-Watson stat	1.854284
Prob(F-statistic)	0.102829		

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

F-statistic	0.635943	Prob. F(2,87)	0.5319
Obs*R-squared	1.296786	Prob. Chi-Square(2)	0.5229
Scaled explained SS	6.845008	Prob. Chi-Square(2)	0.0326

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/31/24 Time: 22:19
Sample: 9/01/2000 12/01/2022
Included observations: 90

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.001621	0.000572	2.832545	0.0057
DR	0.000888	0.000807	1.099335	0.2747
DL_GDP	-0.000675	0.007060	-0.095540	0.9241

R-squared	0.014409	Mean dependent var	0.001594
Adjusted R-squared	-0.008249	S.D. dependent var	0.005388
S.E. of regression	0.005410	Akaike info criterion	-7.568287
Sum squared resid	0.002547	Schwarz criterion	-7.484960
Log likelihood	343.5729	Hannan-Quinn criter.	-7.534685
F-statistic	0.635943	Durbin-Watson stat	2.105679
Prob(F-statistic)	0.531879		

8.10 USA Breusch-Pagan-Godfrey Heteroskedasticity Test EViews Output

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

F-statistic	0.397570	Prob. F(3,84)	0.7551
Obs*R-squared	1.232011	Prob. Chi-Square(3)	0.7453
Scaled explained SS	1.761034	Prob. Chi-Square(3)	0.6235

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/31/24 Time: 22:17
Sample: 3/01/2001 12/01/2022
Included observations: 88

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000668	0.000136	4.897328	0.0000
DR	0.000450	0.000418	1.075723	0.2851
DL_GDP	0.000561	0.009569	0.058674	0.9534
DDL_HPI	0.001220	0.010888	0.112085	0.9110

R-squared	0.014000	Mean dependent var	0.000665
Adjusted R-squared	-0.021214	S.D. dependent var	0.001185
S.E. of regression	0.001197	Akaike info criterion	-10.57302
Sum squared resid	0.000120	Schwarz criterion	-10.46041
Log likelihood	469.2129	Hannan-Quinn criter.	-10.52765
F-statistic	0.397570	Durbin-Watson stat	2.139281
Prob(F-statistic)	0.755085		

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

F-statistic	1.097245	Prob. F(2,87)	0.3384
Obs*R-squared	2.214308	Prob. Chi-Square(2)	0.3305
Scaled explained SS	3.022194	Prob. Chi-Square(2)	0.2207

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 05/31/24 Time: 22:11
Sample: 9/01/2000 12/01/2022
Included observations: 90

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000320	6.07E-05	5.271939	0.0000
DR	0.000270	0.000183	1.481184	0.1422
DL_GDP	-0.000382	0.004302	-0.088764	0.9295

R-squared	0.024603	Mean dependent var	0.000314
Adjusted R-squared	0.002181	S.D. dependent var	0.000539
S.E. of regression	0.000539	Akaike info criterion	-12.18273
Sum squared resid	2.52E-05	Schwarz criterion	-12.09940
Log likelihood	551.2228	Hannan-Quinn criter.	-12.14913
F-statistic	1.097245	Durbin-Watson stat	2.008252
Prob(F-statistic)	0.338363		

8.11 RSA Credit Rationing Null Hypothesis EViews Output

Hypothesis Testing for DR_DIFFERENCE
Date: 05/19/24 Time: 00:29
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments
Test of Hypothesis: Mean = 0.000000

Sample Mean = 0.007537
Sample Std. Dev. = 0.669515

Method	Value	Probability
t-statistic	0.106799	0.9152

8.12 USA Credit Rationing Null Hypothesis EViews Output

Hypothesis Testing for DR_DIFFERENCE
Date: 05/19/24 Time: 00:48
Sample (adjusted): 9/01/2000 12/01/2022
Included observations: 90 after adjustments
Test of Hypothesis: Mean = 0.000000

Sample Mean = -0.008072
Sample Std. Dev. = 0.305196

Method	Value	Probability
t-statistic	-0.250910	0.8025