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*Araştırma Makalesi ● Research Article*

# Granger Causal Linkages Between Economic Growth and Fixed Capital Formation in South Africa: A Frequency Domain Analysis

## *Güney Afrika'da Ekonomik Büyüme ve Sabit Sermaye Oluşumu Arasındaki Granger Nedensel İlişkiler: Bir Frekans Alanı Analizi*

Fela Özbey*

**Abstract:** The purpose of this study is to examine the Granger causal relationships between gross fixed capital formation (GFCF) growth and economic growth in South Africa. To provide a more comprehensive analysis of the Granger causality (GC) relationships between these macroeconomic indicators, this study investigates these causalities in the frequency domain. The methodology is based on decomposing time series into weighted sinusoidal components and performing separate GC tests for each component. Test results reveal that there is feedback between capital formation and economic growth in South Africa in the frequency domain, even at the 1% significance level. Furthermore, the test results indicate that the GC from fixed capital formation to economic growth is detected in lower frequencies compared to the GC from economic growth to capital formation. This means that the severity of the GC from economic growth to capital formation is stronger than the reverse direction GC in South Africa.

**Keywords:** Frequency Domain Granger Causality, Hodrick-Prescott Filter, Bootstrap, Economic Growth, Capital Formation

**Öz:** Bu çalışmanın amacı, Güney Afrika'da sabit sermaye oluşumu ile ekonomik büyüme arasındaki Granger nedensellik ilişkilerinin araştırılmasıdır. Bu makroekonomik göstergeler arasındaki Granger nedensel ilişkilerin daha kapsamlı bir analizini sağlamak için, nedensellikler frekans alanında araştırılmıştır. Yöntem, zaman serilerinin ağırlıklı sinüzoidal bileşenlerine ayrıştırılarak her bir bileşen için ayrı ayrı Granger nedensellik testinin gerçekleştirilmesine dayanmaktadır. Test sonuçları, Güney Afrika'da ekonomik büyüme ile sermaye oluşumu arasında, %1 önem düzeyinde dahi, frekans alanında çift yönlü bir Granger nedenselliğin olduğunu göstermektedir. Ayrıca, çalışma sabit sermaye oluşumundan ekonomik büyümeye olan Granger nedenselliğinin, ekonomik büyümeden sermaye oluşumuna olan Granger nedenselliğe kıyasla daha düşük frekanslarda mevcudiyet gösterdiğini de ortaya koymaktadır. Bu sonuçlar, Güney Afrika'da ekonomik büyümeden sermaye oluşumuna olan Granger nedenselliğin sermaye oluşumundan ekonomik büyümeye olan Granger nedensellikten daha güçlü olduğunu ifade etmektedir.

**Anahtar Kelimeler:** Frekans Alanında Granger Nedensellik, Hodrick-Prescott Filtresi, Bootstrap, Ekonomik Büyüme, Sermaye Oluşumu

*Asst. Prof. Dr., Çukurova University, Faculty of Economics and Administrative Sciences, Department of Econometrics, fozbey@cu.edu.tr, ORCID: 0000-0003-1468-6106

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## Introduction

Although South Africa is the second largest economy in sub-Saharan Africa, it has faced several macroeconomic challenges in recent years, including slow economic growth and reduced investment. Like many other nations, the South African economy was negatively impacted by both the Covid-19 pandemic, and the Russian occupation of Ukraine. According to the International Monetary Fund (2023), South Africa's growth will continue to slow down in 2023 due to increased power cuts, a less favorable external environment, and adverse effects stemming from the growth slowdown experienced in late 2022. Nonetheless, despite these disadvantages, capital formation is projected to contribute to enhancing economic growth (Pasara & Garidzirai, 2020).

GFCF represents the total domestic investment in physical assets such as infrastructure, technology, machinery, and equipment. It is considered a key driver of economic growth because investment in new capital goods increases the productive capacity of the economy. Upgrading machinery and technology can lead to higher output, lower production costs, and improved competitiveness. Furthermore, infrastructure projects such as ports, roads, bridges, and utilities not only support economic activities directly but also create an enabling environment for businesses to thrive. Well-developed infrastructure attracts investment, enhances productivity, and fosters trade. Moreover, GFCF has a multiplier effect by creating demand for goods and services that also affects other sectors and thus increases economic activity ripples through the economy. On the other hand, economic growth can also affect investment decisions because the propensity to invest generally increases when economic growth prospects are high. Taraki & Arslan (2019) provide a broad overview of the theoretical literature on capital formation and the capital formation - economic growth nexus within the framework of these theories.

One crucial research problem in econometrics is identifying and analyzing interactions among multiple time series recorded simultaneously. Empirical investigations of such dynamic interrelationships between multiple time series are widely conducted using GC analysis, named after Granger (1969). GC refers to the ability of one variable to improve the forecast of another one. Another way for detecting the GC is using the measure of (unconditional) causality proposed by Geweke (1982), which also is suitable for addressing causality in the frequency domain. Using the approach of Geweke (1982), Breitung & Candelon (2006) propose a parametric testing procedure to test the GC in the frequency domain. Farné & Montanari (2022) propose a different frequency domain testing approach in which the benchmark is the GC spectrum under the null of stochastic independence. In frequency domain GC analysis, (stationary) processes are expressed as a sum of weighted sinusoidal components with a specific frequency. This decomposition allows for analyzing slow and fast fluctuating components separately and determining the frequencies at which the predictive power is concentrated. Thus, instead of performing a single test for the whole relationship, it is performed separately for each component because the direction and strength of the GC may differ among frequencies (Croux & Reusens, 2013). Thus, this testing methodology offers greater flexibility and allows for a more in-depth analysis.

Existing empirical studies investigating the GCs between economic growth and capital formation are mainly focused on the time domain. Employing the recently proposed methodology of Farné & Montanari (2022), this study contributes to the literature by investigating these causalities for South Africa in the frequency domain and by determining the direction and strength of the GCs for slow and fast fluctuating components separately.

The organization of this paper is as follows. Section 1 summarizes the previous studies and their findings. Section 2 describes the data and filters used, as well as the methodology of the GC test in frequency domain via bootstrap. Section 3 reports the empirical results. The last section discusses the findings of this investigation, juxtaposing them with the existing literature, and concludes.

## 1. Previous Studies

Using quarterly data, Ncanywa & Makhenyane (2016) investigate the relationships between GFCF and economic growth for South Africa covering the period between 1960-Q1 and 2014-Q4. The cointegration analysis reveals positive relationship in both the long and the short-run. GC test results indicate a feedback (bidirectional GC). Meyer & Sanusi (2019) perform a similar analysis for the period between 1995-Q1 and 2016-Q4 to investigate the relationships between GFCF, employment and economic growth. They detect a long run relationship between variables as well as a unidirectional GC from economic growth to GFCF.

Pasara & Garidzirai (2020) conduct a vector autoregression (VAR) analysis and perform the conventional GC test to investigate relationships between unemployment, economic growth and GFCF in South Africa for the period from 1980 to 2018. They find a unidirectional GC from economic growth to GFCF.

Performing a panel data analysis and using annual data from 1997 to 2017, Kong, Nketia, Antwi & Musah (2020) study the relationships between financial development, GFCF, and economic growth for 39 African countries, including South Africa. They conclude that GFCF has a positive impact on economic growth and there exists bidirectional causality between these two variables.

Kesar, Bandi, Jena & Yadav (2023) conduct a panel data analysis on BRICS countries using annual data from 2002 to 2019. Their research aims to explore the GC between GFCF, governance index, and economic growth. The study identifies a unidirectional GC from growth to GFCF.

In summary, all these studies confirm that economic growth has a Granger causal effect on gross capital formation in South Africa. Furthermore, some of these studies also demonstrate GC from gross capital formation to economic growth. But it is worth emphasizing that all of these studies were conducted using the conventional time domain-GC test.

## 2. Data and Methodology

### 2.1. Data

Quarterly data covering the period between 1993-Q1 and 2019-Q4 are used to investigate the frequency domain GCs between economic growth and GFCF growth in South Africa. Economic activities are represented by gross domestic product (GDP). Data are retrieved from the IFS database of IMF (data.imf.org). Both series are seasonally adjusted and realized expressed in the 2015 base-year domestic currency. Logarithmic transformations are performed using natural logarithms to linearize series.

### 2.2. Testing stationarity of the series

Since the GC testing procedures used in this study requires stationary series, the conventional Augmented Dickey-Fuller (ADF) test of Dickey & Fuller (1979, 1981) is performed to test the presence of stochastic and deterministic trends in the logarithmic transformations of the original series.

### 2.3. Filtering the series

To remove the stochastic trends, the Hodrick-Prescott (HP) filter named after Hodrick & Prescott (1997) is applied. The HP filter extracts the cyclical component as (Baxter & King, 1999):

$$\tilde{y}_t = \left( \frac{\eta(1-L)^2(1-L^{-1})^2}{1+\eta(1-L)^2(1-L^{-1})^2} \right) y_t \, . \tag{1}$$

Here $\tilde{y}_t$ is the cyclical component of $y_t$ and $\eta$ is the penalty parameter used to control the variation of the growth component. Following the recommendation of Hodrick & Prescott (1997) for quarterly data, $\eta = 1600$ is applied.

There are several reasons why the HP filter is preferred over (first-)differencing. As shown by Baxter & King (1999), first-differencing tends to produce more volatile time series than other filters, introduces a phase shift in the filtered series, and reweights the frequencies considerably. On the other hand the HP filter is symmetrical (i.e., there is no phase shift), approximates Baxter and King's high-pass filter remarkably well (particularly for quarterly data), and is able to remove up to 4 stochastic trends without loss of observations.

### 2.4. Granger Causality test in frequency domain via bootstrap

A VAR(p) representation determining the relationships between $x_{1t}$ and $x_{2t}$ is in the form:

$$\Phi_p(L)x_t = \varepsilon_t \tag{2}$$

where, $\Phi_p(L)$ is a $2\times 2$ sized p order polynomial of the lag operator, $x_t = \left[x_{1t}, x_{2t}\right]'$, and $\varepsilon_t$ is vector of white nose errors having a $2\times 2$ positive definite variance matrix $\Sigma = \left[\sigma_{ij}\right]$.

Granger (1969) defines the unidirectional causality from $x_{2t}$ to $x_{1t}$ ($x_{2t} \Rightarrow x_{1t}$) as:

$$MSE(\hat{x}_{1t} \mid x_{1t-1},\ldots,x_{1t-p},x_{2t-1},\ldots,x_{2t-p}) < MSE(\hat{x}_{1t} \mid x_{1t-1},\ldots,x_{1t-p}) . \tag{3}$$

Here $MSE$ stands for mean squared error. It is obvious that as long as the estimates are unbiased, $MSE$ also refers to the variance of the related model. This definition implies that $x_{1t}$ can be better forecast by using the past values of $x_{2t}$ besides the past values of $x_{1t}$ instead of using only the past values of $x_{1t}$. In other words, if past values of $x_{2t}$ help improving the forecast of $x_{1t}$, $x_{2t}$ is causal to $x_{1t}$ in Granger sense.

In time domain, the definitions of (unidirectional) GC from $x_{2t}$ to $x_{1t}$ refers to having at least one $(1,2)$-th nonzero element of matrices $\Phi_j$, $j = 1,2,\ldots p$. Thus, Granger (non)causality from $x_{2t}$ to $x_{1t}$ can be test by testing the null of

$$\phi_{12}^{(1)} = \phi_{12}^{(2)} = \ldots = \phi_{12}^{(p)} \tag{4}$$

via Wald (1943) test. Similarly, testing for Granger (non)causality from $x_{1t}$ to $x_{2t}$ requires testing the null of

$$\phi_{21}^{(1)} = \phi_{21}^{(2)} = \ldots = \phi_{21}^{(p)} . \tag{5}$$

Here, $\phi_{12}^{(j)}$ is the $(1,2)$-th and $\phi_{21}^{(j)}$ is the $(2,1)$-th element of the coefficient matrix $\Phi_j$.

Another way for detecting the GC is using the measure of (unconditional) causality proposed by Geweke (1982), which is based on the condition given in (3). This measure is defined as a log likelihood ratio:

$$M_{x_2 \Rightarrow x_1} = \ln\left(\frac{MSE(\hat{x}_{1t} \mid x_{1t-1},\ldots,x_{1t-p})}{MSE(\hat{x}_{1t} \mid x_{1t-1},\ldots,x_{1t-p},x_{2t-1},\ldots,x_{2t-p})}\right). \tag{6}$$

Geweke (1982) shows that besides the time domain, the measure given in (6) is also suitable for addressing causality in the frequency domain. Using the approach of Geweke (1982), Breitung & Candelon (2006) propose a parametric testing procedure to test the GC in the frequency domain.

Contrary to the conventional testing procedures, Farné & Montanari (2022) propose a different approach in which the benchmark is the GC spectrum under the null of stochastic independence. In this method, to express the frequency domain components of the series, for each frequency $\omega$, the transfer function of invertible process given in (2) is defined as:

$$f(\omega)=\left(I-\sum_{j=1}^{p}\Phi_j e^{-ij\omega}\right)^{-1}, \quad -\pi\le\omega\le\pi \,. \tag{7}$$

Thus, the model-based spectrum $h(\omega)$ is defined as:

$$h(\omega)=f(\omega)\Sigma f(\omega)^*, \tag{8}$$

where $f(\omega)^*$ is the complex conjugate transpose of $f(\omega)$.

Because VAR models are (mostly) seemingly unrelated regressions (SUR), the elements of the error terms vector $\varepsilon_t$ are not (necessarily) independent (i.e., $Cov(\varepsilon_{1t},\varepsilon_{2t})\neq 0$). It means that their variance matrix $\Sigma$ is not a diagonal matrix. Following Geweke (1982) and Ding, Chen & Bressler (2006), to orthogonalize the elements of the inverted $x_t$ process, Farné & Montanari (2022) use the $\Sigma = PDP'$ decomposition of the variance matrix $\Sigma$. Here, $D$ is a (positive definite) diagonal matrix and $P$ is a lower triangular matrix having $p_{21}=\sigma_{21}/\sigma_{11}$ and diagonal elements equal to 1.

Transforming the transfer function $f(\omega)$ such that $\tilde{f}(\omega)=f(\omega)P^{-1}$ and using this transformation to orthogonalize the process $x_t$, produces the process $\tilde{x}_t=\tilde{f}(\omega)x_t$. Keeping in mind that $\tilde{f}(\omega)$ and $h(\omega)$ are matrices in forms:

$$\tilde{f}(\omega)=\begin{bmatrix}\tilde{f}_{11}(\omega) & \tilde{f}_{12}(\omega)\\ \tilde{f}_{21}(\omega) & \tilde{f}_{22}(\omega)\end{bmatrix} \text{ and } h(\omega)=\begin{bmatrix}h_{11}(\omega) & h_{12}(\omega)\\ h_{21}(\omega) & h_{22}(\omega)\end{bmatrix}, \tag{9}$$

the GC spectrum of $x_{1t}$ with respect to $x_{2t}$, by the definition of Geweke (1982), turns to:

$$h_{x_2\to x_1}(\omega)=\ln\left(\frac{h_{11}(\omega)}{\sigma_{11}\left|\tilde{f}_{11}(\omega)\right|^2}\right). \tag{10}$$

This spectrum displays how strong the relationship is between the past values of $x_2$ and present value of $x_1$ at frequency $\omega$. Therefore, in the approach of Farné & Montanari (2022), at each frequency $\omega$, the null of $h_{x_2\to x_1}(\omega)=0$ is tested under the assumption that $x_{1t}$ and $x_{2t}$ are independent. Farné & Montanari (2022), stress that this testing procedure for GC in the frequency domain is more complicated than in the time domain. They suggest using of the bootstrap method of Politis & Romano (1994) to approximate the distribution of the null.

## 3. Findings

Analyses of this study are performed using R (R Core Team, 2023) packages urca (Pfaff, 2008a), tseries (Trapletti & Hornik, 2023), mFilter (Balcilar, 2019), vars (Pfaff, 2008b), and grangers (Farnè & Montanari, 2019, 2022).

As it is mentioned before, natural logarithms are used to linearize series. Logarithmic transformations of GDP and GFCF are denoted as LGDP and LGFCF, respectively. The graphs of these transformations are given below in Figure 1.

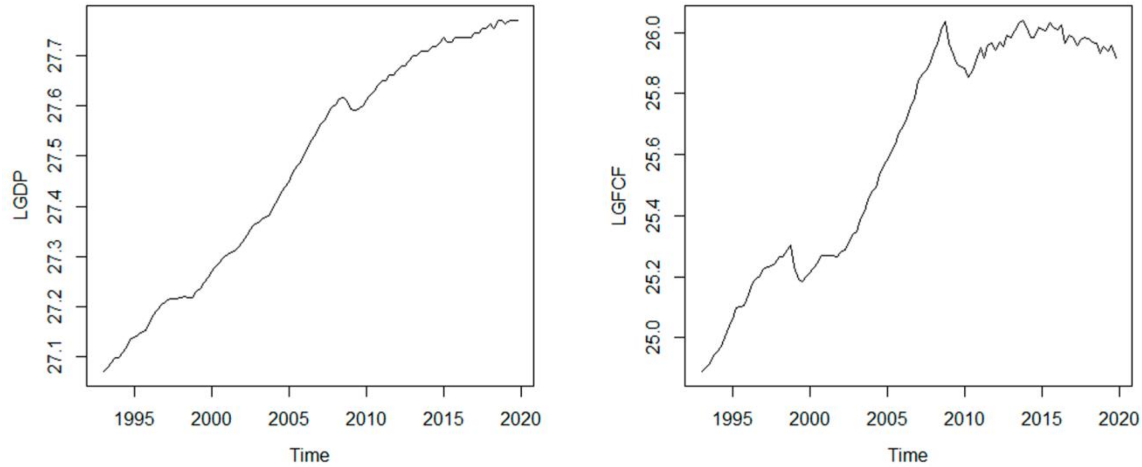


**Figure 1.** Graphs of Logarithmic Transformations of LGDP and LGFCF.

The frequency domain GC testing procedures of Farné & Montanari (2022) (hereafter FMGC) used in this study requires stationary series. Stationarity of the logarithmic series is tested using the conventional ADF test. Because it is apparent from the graphs that series contain deterministic components, tests are performed using testing models with deterministic components – the model with trend and intercept and the model with intercept. The results are reported in Table 1.

**Table 1.** ADF Test Results for Logarithmic Transformations

| Series | Trend and Intercept | | | Intercept | |
|---|---|---|---|---|---|
| | $\hat{\tau}_\tau$ | $\hat{\Phi}_2$ | $\hat{\Phi}_3$ | $\hat{\tau}_\mu$ | $\hat{\Phi}_1$ |
| LGDP | 0.2165 | 11.2736*** | 2.7020 | -2.2564 | 16.845*** |
| LGFCF | -0.1343 | 4.3388* | 2.7558 | -2.2640 | 6.3366** |

*p<.10, **p<.05, and ***p<.01

$\hat{\tau}$'s are t-like statistics distributed as in Fuller (1996, p.642) and $\hat{\Phi}$'s are F-like statistics distributed as in Dickey & Fuller (1981, p.1063). ADF test results indicate that both series contain a stochastic trend and a drift. Following Farné & Montanari (2022), the HP filter is applied to remove the stochastic trends. Since series are drifted, the drift adjustment feature of the mFilter library (for details, see Balcilar, 2019) is activated. Filtered series are denoted LGDP_HP and LGFCF_HP. The graphs of decomposed trend and filtered series are given in Figure 2.

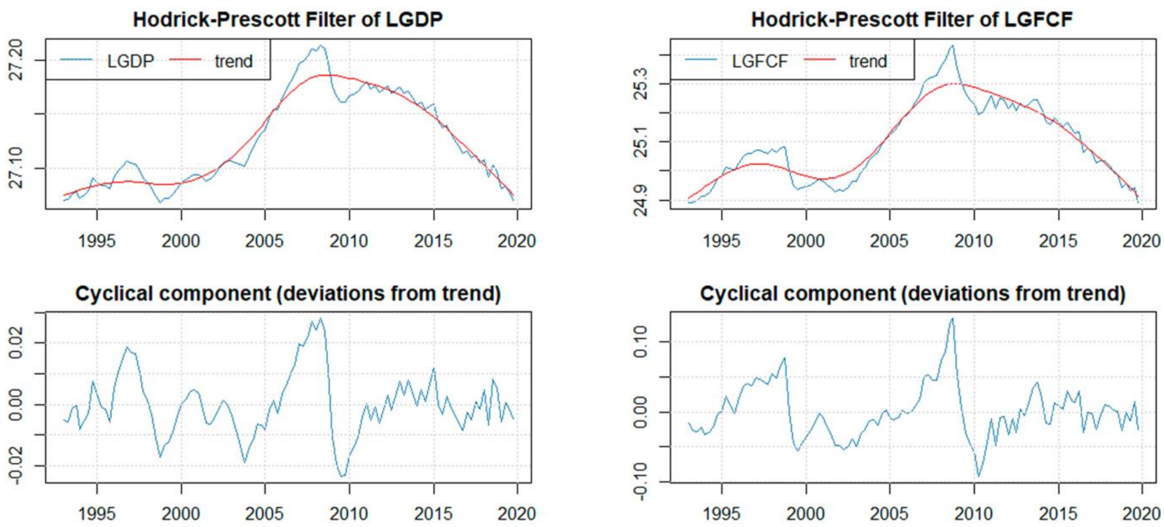

**Figure 2.** Graphs of Decomposed Series LGDP and LGFCF.

Table 2 presents the results of the stationarity tests for the filtered series LGDP_HP and LGFCF_HP. These series are detrended using the HP filter; therefore, their stationarities are examined using testing models with and without an intercept. Test results indicate that both HP-filtered series are stationary and fulfilled the requirement of the FMGC approach.

**Table 2.** ADF Test Results for HP-Filtered Series

| Series | Intercept | None |
|---|---|---|
| | $\hat{\tau}_{\mu}$ | $\hat{\tau}$ |
| LGDP_HP | -3.3792** | -3.3953*** |
| LGFCF_HP | -3.3888** | -3.4051*** |

*p<.10, **p<.05, and ***p<.01

The FMGC test is performed for each frequency $\omega = s/T$, $s = 1,2,\ldots,54$ and $T = 108$ (the number of observations). Bootstraps are conducted with 1000 replications, and the seed number is set to be 123. Test results are reported in Table 3. The graphical illustrations of the results are given in Figure 3.

**Table 3.** FMGC Test Results

| FMGC Direction | Raw | | | Under the Bonferroni Correction | | |
|---|---|---|---|---|---|---|
| | Quantile | Threshold | Sig. Freq. | Quantile | Threshold | Sig. Freq. |
| LGFCF_HP to LGDP_HP | 90% | 0.0478 | 1/108 - 14/108 | 99.81% | 0.1580 | 1/108 - 4/108 |
| | 95% | 0.0668 | 1/108 - 11/108 | 99.91% | 0.1696 | 1/108 - 4/108 |
| | 99% | 0.1056 | 1/108 - 7/108 | 99.98% | 0.2252 | none |
| LGDP_HP to LGFCF_HP | 90% | 0.0459 | 1/108 - 36/108 | 99.81% | 0.1448 | 1/108 - 17/108 |
| | 95% | 0.0653 | 1/108 - 28/108 | 99.91% | 0.1492 | 1/108 - 16/108 |
| | 99% | 0.1193 | 1/108 - 19/108 | 99.98% | 0.1890 | 1/108 - 14/108 |

The test results for the GC from GFCF growth to economic growth are reported in the top section of Table 3. The bootstrapped threshold for the FMGC test at the 95% confidence level is 0.0668. Test results for this quantile indicate that GFCF growth Granger causes economic growth across frequencies ranging from 1/108 to 11/108. The Bonferroni-corrected-quantile is 99.91%, with a corresponding threshold value of 0.1696 (the equivalent threshold for the overall test). The corrected spectrum of statistically significant GCs from GFCF growth to economic growth consists of frequencies between 1/108 and 4/108.

In the lower section of Table 3, the test results for the GC from economic growth to GFCF growth are presented. The FMGC test has a bootstrapped threshold of 0.0653 at a 95% confidence level. The test results reveal that economic growth Granger causes GFCF growth at frequencies ranging from 1/108 to 28/108. Additionally, for the corresponding overall Bonferroni-corrected test (quantile of 99.91%), the threshold value is 0.1492 and the spectrum of statistically significant GCs from economic growth to GFCF growth is found between frequencies 1/108 and 16/108.

Overall, it is concluded that there are bidirectional Granger causal relationships in the frequency domain between economic growth and GFCF growth, even at the 1% significance level.

Figure 3 displays graphical representations of the test results for GC, with the top section illustrating the causality from GFCF growth to economic growth and the bottom section showing the GC from economic growth to GFCF growth. The horizontal lines represent bootstrapped thresholds.

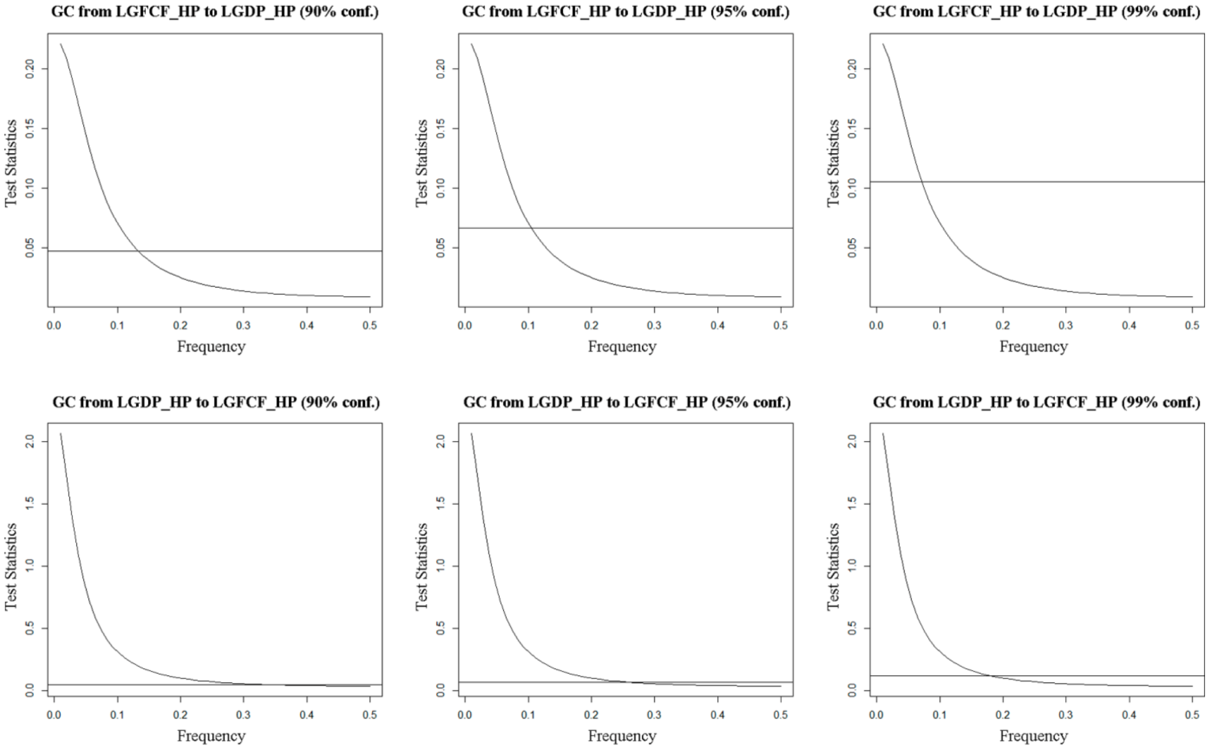


**Figure 3:** Graphical Illustrations of the FMGC Test Results

## Discussion and Conclusion

Previous empirical studies investigating the GCs between capital formation and economic growth in South Africa are conducted in the time domain using the conventional GC test. These studies confirm that economic growth has a Granger causal effect on gross capital formation in South Africa. Furthermore, some studies also confirm GC from gross capital formation to economic growth, demonstrating feedback.

This study takes a different approach by examining these causalities in the frequency domain, where processes are decomposed into weighted sinusoidal components to separate slow and fast fluctuations. Then, to identify components with predictive power, separate GC tests are performed for each frequency. Test results indicate that there is feedback between GFCF growth and economic growth in South Africa in the frequency domain, even at the 1% significance level. Our findings are consistent with the results obtained by Ncanywa & Makhenyane (2016) and Kong et al. (2020) in the time domain. Additionally, test results indicate that the GC from GFCF growth to economic growth is detected in lower frequencies compared to the GC from economic growth to GFCF growth. This could be a reason why some of studies conducting the time domain - GC test could not detect GC from GFCF growth to economic growth.

As a conclusion, the severity of the GC from economic growth to GFCF growth is stronger than the reverse direction in South Africa. Because the causal link from GFCF growth to economic growth is weaker, it is possible that it could not be detected by conducting the time domain - GC test. Therefore, in order to conduct a more comprehensive examination of GC relationships between variables, it is suggested to be performed a frequency domain investigation.

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