Leading the Economy

Do both the banking sector and stock market development independently lead economic activity in South Africa? Evidence from South Africa using Granger-causality tests

By

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The other part of the requirement for this qualification was the completion of a programme of courses. I hereby declare that I have read and understood the regulations governing the submission of Master of Commerce dissertations, including those relating to length and plagiarism, as contained in the rules of the University, and that this dissertation conforms to those regulations.

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Abstract

This study investigates and concludes on thus the predictability of economic activity in South Africa through the use of share price indices and banking sector asset levels as leading indicators.

This study investigates share price and banking sector information using both nominal and real quarterly and monthly time-series data for the period March 1998 to October 2017. For share prices analysis, it takes market segmentation on the JSE into account, and examines causality between the All-Share index, the Industrial index, the Resources index and the Financial index against GDP and the index of Industrial Production (IIP) using the test proposed by Granger (1969). For the banking sector development analysis, it takes the South African Reserve Bank's disclosure of all banking institution assets and examines if changes in those asset levels Granger-cause the changes to GDP and IIP.

This study builds on the work performed by previous studies, specifically on Sayed, Auret and Page (2017) and Har, Ee, and Tan (2009), which test the leading relationship of the stock market for economic activity. This study adopts a similar approach to these studies, while also making certain adjustments and additions to their methodology, aiming to produce more robust findings. This study not only tests for a new relationship between banking development and economic activity, but it also conducts several additional stationarity tests to provide more conclusive evidence of the data's stationarity before Granger-causality testing is performed. The additional stationarity tests in this study establish that some time series data, which Sayed et al. (2017) concluded to be stationary, is in fact not stationary, and this contrary finding directly impacts the subsequent Granger-causality testing and results. This study also notes and corrects Sayed et al.'s (2017) methodology which fails to perform subsequent stationarity testing on its differenced time series data, and thus fails to prove that the transformed data is satisfactorily stationary and acceptable for Granger-causality testing. Another adjustment we make to the methodology is the interpretation of the Index for Industrial Production (IIP), which we view as a volume based index rather than a price based index that can be adjusted for inflation, which was the position of Sayed et al. (2017).

The empirical investigation of this study reveals some positive evidence in favour of the JSE as a leading indicator of economic activity, where unidirectional causality is established between the four market segmentation proxies and the macroeconomic variables. This is however less conclusive than the findings of previous South African studies, which is explained. For the banking sector's development analysis, the empirical tests produce inconsistent findings across monthly and quarterly data, leaving one unable to confirm a causal relationship existing between the banking sector's development and economic activity.

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Chapter 1: Introduction

In the world of finance it is largely accepted that a share price of a company is influenced by its future value creation prospects. As a result of its forward-looking nature, the stock market has been proven to be a leading indicator of economic activity in developed markets (Fama, 1990). This finding means that if investment sentiment is high, based on positive future value outlook, there will be a higher stock market index, which will be a forerunner for increased economic activity to come in the future.

If the stock market index serves as a leading indicator for economic activity because of its inherent forward looking nature, it is also worth investigating whether a similar relationship holds for the banking sector and economic activity. More specifically, whether the rise of banking activity could also be a leading indicator of economic activity, and similarly, whether the change in the level of institutional banking assets precedes economic activity changes. Previous studies have also shown this to be true in developed and developing markets. Levine, et. al (2000) test the relationship across 74 countries and find a positive association of financial development and economic growth, while Neusser & Kugler (1998) test the relationship for OECD countries to find a similar relationship.

When comparing the stock market and banking development as leading indicators, the prevailing research argues that, because banks and stock markets affect economic outcomes through different channels, their effectiveness as leading indicators depends on a host of country-specific factors (Peia & Roszbach, 2015).

Thus, to some degree, we recognise that banking development and stock market changes are useful indicators for economic forecasts, particularly in developed economies. This study recognises that there is a gap in literature regarding these relationships within the developing economy of South Africa. The current gap exists due to the low volume of research in this area, which inherently also presents the risk of potential inaccuracies in the findings to date.

This study therefore investigates whether the South African stock market and the banking sector development hold weight in forecasts for future economic growth, and whether one of the variables is perhaps more valuable as a forecasting tool than the other. In the attempt to close the literature gap in this area, this study will address the banking sector's relationship with economic activity in South Africa for the first time, and it will also interrogate and correct the existing inaccuracies of the current findings relating to the stock market's causal relationship with economic activity.

Closing the gap in the literature is important because if these relationships are established, it may have implications for policy makers in South Africa. The existence of these relationships would result in the need for more due attention towards the inputs of these leading indicators in order to potentially control and even grow the South African economy. This could have far reaching long term impacts.

This study will go on to show how prevailing research has developed many theories, which explain the relationships of the stock market and the banking sector with economic activity. It will then look to establish which developed theory suitably fits the South African context, as well as provide room for future research to propose how to utilise these (proven) relationships to manage economic growth in South Africa.

1.1. Research Problem Statement, Objective and Aim

1.1.1. Research Problem Statement

By gaining clarity as to whether the banking sector's or the stock market's development can help predict future economic growth, one can potentially play a role in alleviating South Africa's considerable unemployment problem.

South Africa currently faces widespread unemployment, with the official rate hovering around 20–25% for most of the years from 1991 to 2016 (Vermeulen, 2017), and more recent data from Statistics South Africa indicating a rate of 26.7% for the final quarter of 2017. This is clearly a concern for the all stakeholders affected – whether it is those individuals who are burdened by the difficult life experience unemployment, or the general society which is left with unrest and the potential costs (of increased crime for example), or the country's treasury and corporate sector which aim to help fund the basic needs of those unemployed. The clear solution to unemployment is job creation which is a natural by-product of good economic growth. Conversely, job losses and high unemployment are a result of low or poor economic growth.

Therefore, the acknowledgement of South Africa's gross unemployment issue provides a foundation to justify the importance of any leading indicators of economic activity. Those leading indicators could assist economic policy-setters to foresee possible economic trends and thus intervene to manage good economic growth and consequently reduce the unemployment crisis.

This study recognises the importance of establishing whether the banking sector and stock market development can lead economic growth and thus assist policy setters going forward. Currently these relationships have not been investigated sufficiently in South Africa, which provides reason to close the gap in existing knowledge through this study. Firstly, there is no existing research that investigates the ability for the South African banking sector development to lead economic activity. This paper tests this relationship for the first time. Secondly, the existing research that investigates the stock market's ability to lead economic growth in South Africa is light and therefore open to interrogation. This paper finds inaccuracies in the methodology and thus findings of Sayed et al. (2017) and provides corrected findings to close the gap. This is detailed in chapter 4.3.3.

1.1.2. Objective and Aim

The objective of this paper is to find a solution to alleviate the unemployment crisis in South Africa. This study suggests that managing economic growth, through the controls associated with the development of the stock market and banking sector, would serve to control the unemployment rate, considering that good economic growth stimulates job creation and the reduction of unemployment.

This study therefore aims to confirm the existence of leading indicators of economic activity in order for those leading indicator relationships to be leveraged to control growth and improve the unemployment crisis in South Africa. If one was to establish that there are variables that lead changes in economic activity then there is the opportunity to utilise these predictive relationships to avoid any expected economic downturns and potentially stimulate economic upturn. The first step, however, would be to establish if there are such relationships to leverage off. This study recognises two potential leading indicators of economic activity, being that of the activity of the stock market as well as the development within the banking sector.

The United States saw the most recent economic downturn come in the wake of its 2007 financial crisis. The cause of the crisis is well known for being the bubble of sub-prime lending, which inflated property prices and debt exposure to unsustainable levels. The ballooning demand for debt saw risky debt instruments re-packaged in the form of other investments, which stimulated heightened (incorrectly calculated) risk in the whole market. The unsustainability of this environment led to the banking sector imploding and asset prices plunging sharply. Reinhart and Rogoff (2008) point out that these issues of asset price inflation and rising leverage are indicators of a potential financial crisis. Importantly, Reinhart and Rogoff (2009) went on to show that the consequences of the 2007 financial crisis included a deflated equity market as well as severe downturn in economic output and employment, providing reason to believe that such a predictive link exists between the stock market and economic growth.

South Africa’s stock market has also experienced sharp falls in the past as it did when the technology bubble popped after 2000 as well as when it felt the strong knock-on effects of the global financial crisis of 2007, where the same outcome of an economic downturn were clear. In addition, South Africa has also seen its relatively strong banking sector under pressure through the failure of African Bank and VBS Bank. Such large banking failures are linked to consequences like a credit rating downgrade for South Africa, tightening of the debt markets due to liquidity concerns, and heightened caution of any retailers undergoing credit sales. Such consequences have a far reaching impact for South Africa and this should incentivise strong and sound management to avoid such outcomes.

It is clear that South Africa is exposed to such stock market and banking sector failures, however, what is not empirically clear at this stage is whether these failures have a clear relationship with economic failure as a result. If it was established that stock market or banking sector changes were leading indicators of economic activity in South Africa, there would be added impetus for policy-makers to use those indicators to prevent such failures to occur, and thus protect the economy of the country.

A recent South African study investigated the relationship between the stock market development and economic activity (Sayed et al., 2017) and our work aims to add further insights and findings, as well as investigate an additional relationship between banking development and economic activity.

The detailed aim of this study is to prove whether the banking sector and the stock market's development and growth both have a causal relationship with future economic growth. It will measure the changes in banking sector development (measured by the changes in the total assets of the South African Banking Institutions) (referred to as '*BANKDEV' for the rest of the paper*) as well as the changes in equity prices (on four different share indices on the JSE; All-Share [*ALSI*], Industrial [*INDI*], Resource [*RESI*] and Financial indices [*FINI*]), and their independent ability to lead economic activity (measured by the growth rate of the South African Gross Domestic Product (*GDP*) and/or the growth rate of the Index of Industrial Production [*IIP*]).

Thus, with the use of pairwise causality tests proposed by Granger (1969), the paper will explore the causal relationships between

1. BANKDEV against gross GDP and the IIP in South Africa and
2. Each share index (ALSI, INDI, RESI, FINI) against gross GDP and the IIP in South Africa.

Unidirectional causality in both cases will be tested, providing a conclusion on whether or not the banking sector and stock market both lead economic activity in South Africa.

The research will be quantitative in nature as the extensive data is collected, analysed and interpreted through the use of statistical testing.

Ultimately, if a causal relationship can be established between the stock market and/or banking sector development and economic growth, there is scope to control economic growth through the inputs of those predictive variables and thus reduce the unemployment rate in South Africa.

1.2. Research Question

The core research question of this study is whether there is a causal and statistically significant relationship in South Africa between:

1. The banking sector's development and economic activity and
2. The stock market development and economic activity.

The two independent null hypotheses are that neither the banking sector's asset levels, nor share prices on the JSE, lead economic activity in South Africa. The alternative hypotheses are that those same variables do in fact lead economic activity in South Africa.

The remainder of this proposal will go on to address the current literature on the banking sector and stock market's relationship to economic activity in chapter 2, the data and methods for the study in chapter 3, the results and analysis provided in chapter 4 and finally the conclusion of the study in chapter 5. Each chapter's subsections are correspondingly numbered according to their respective chapter and sections therein.

Chapter 2: Literature Review

Chapter 2.1 will focus on the existing literature surrounding the proven relationships between stock markets and economic activity, while chapter 2.2 will do the same for the proven relationships between financial development and economic activity. Both of these chapters will explore any resulting theories that have developed from these found relationships, while they will also highlight the contexts where no such relationships have been found to exist. Chapter 2.3 will then focus on where the prevailing research leaves gaps for this study to fill – namely the lack of South African focus and the arguable findings of existing studies.

2.1. The Stock Market and Economic Activity

2.1.1. Empirical Findings of an Existing Relationship

The stock market is said to be a leading indicator of economic activity based on several theories. It is seen as the most important market with respect to corporate investment decisions (Auret & Golding, 2012), which drives economic growth. Comincioli (1996) indicated that two of the main theories were that of the 'wealth effect' and the theory of the traditional valuation model of stock prices.

The ‘wealth effect’ theory proposes that the stock market actually causes economic activity based on the fact that an overall high share portfolio level produces higher consumer spending. Where a consumer feels their ‘wealth’ they are more inclined to spend it and drive growth. This effect was proven to be found in 16 emerging markets over the period of 1985 – 2000, where a statistically significant link was found between private consumption growth and stock returns (Funke, 2004).

On the other hand, the traditional valuation model indicates that the share price is a reflection on expectations of future performance of the corresponding company. When one considers that the stock market represents a multitude of companies’ share prices, it is fair to therefore say that the stock market is a reflection of the future performance of the broader economy. Thus, any change in the stock market level is indicative of a future change in economic activity. This is illustrated by different valuation techniques, such as the Gordon model, which indicates that a company’s share price today can be expressed as the present value of an infinite flow of dividends in the future (Gordon, 1959), as well as the ‘discounted cash flow’ model, which forecasts the company’s performance and discounts those future performance cash flows to the present time in order to estimate the present value of the company. Both of these valuation models make use of a company’s future performance to arrive at their present value, and are thus inherently forward-looking and helpful leading indicators of economic activity. Stock and Watson (2003) supported this in their findings of stock prices being one of the few favourable metrics that indicated the trend of a financial downturn in 2001. As much as the financial crisis of 2001 could not be fully predicted, stock returns (along with term spreads and unemployment claims) proved to have the most value as leading indicators.

There are at least two additional theories for why stock prices lead economic activity. The first being the effect of the company’s share price on its weighted average cost of capital and the follow-on impact on economic activity. In this case, a high share price is consistent with a lower cost of equity for companies (and thus a lower investment hurdle rate), which would ultimately lead to the attractiveness of further capital projects and thus increased economic activity (Ikoku & Alvan, 2010). The second additional theory suggests that a high share price is a financial accelerator for investment due to its ability to improve a company’s creditworthiness and thus its cost of borrowing (Bernanke, Gertler, & Gilchrist, 1996).

Various different research findings over the years have confirmed the leading relationship that stock prices have with economic activity. Starting in the developed market of the United States, Fama (1981) found evidence of real stock returns being positively related to measures of real economic activity like capital expenditure. Then, in 1983, it was established that the S&P 500 saw stocks decline before economic recessions and trend upwards before the beginning of economic expansion (Pearce, 1983).

Barro (1990) then found strong evidence of stock prices having substantial explanatory power for subsequent U.S. investment, and thus explanatory power of economic activity. Stock returns have also been found to Granger-cause a substantial fraction of the variance in real economic activity of the U.S. economy through the use of a VAR (vector-autoregression) analysis (Lee, 1992), which is a similar methodology applied in this study to South Africa. Comicioli (1996) established that during the period 1970 (quarter 1) to 1994 (quarter 3) there was a causal relationship (based on Granger testing) between the growth rate of stock prices and the growth rate in the economy. It is, however, noted that the economic cycles covered by this study differ significantly without the effects of the financial crises of 2000 and 2007. Foresti (2006) also confirmed the above findings within the U.S. with the verdict that stock prices can predict short and medium term macroeconomic growth.

Similar studies come from a variety of different countries with inherently different states of economic development. Bahadur & Neupane (2006) provide empirical evidence of long-run integration and causality of macroeconomic variables and stock market indicators (in real terms) in the small capital market of Nepal. It depicts that the stock market plays significant role in determining economic growth in Nepal and vice versa. This study will therefore make use of nominal and real data in its analysis. In Malaysia, results show that the stock market Granger-cause economic activity with no reverse causality observed (Har et al., 2009), while Pilinkus & Donatas (2009) proved that, in Lithuania, some macroeconomic variables (e.g., GDP, material investment, construction volume index, etc.) are led by the Lithuanian stock market index (OMXV). A Nigerian study performed a similar study to this paper as it aimed to confirm causal relationships among stock market prices, real GDP and the index of industrial. Through the use of Granger testing, it finds that bidirectional causality exists between stock prices and GDP but no causality between stock prices and industrial production in Nigeria (Ikoku & Alvan, 2010).

A far-reaching 2017 study obtained data from Jan 1994 – December 2014 for twenty industrial markets to test the relationship between stock market activities and industrial production growth. The markets included six advanced economies (Canada, France, Germany, Italy, United Kingdom, United States); four Scandinavian economies (Denmark, Norway, Finland Sweden); five emerging economies (Brazil, Russia, India, China, South Africa); and five industrial (semi industrial) Asian markets (South Korea, Japan, Singapore, Thailand, and Taiwan). The overall outcome of the Granger testing in this extensive study found there to be a unidirectional causation from stock market returns to industrial growth in all these markets (Chiang & Chen, 2017).

In South Africa specifically, the relationship between the local stock market (the JSE) and economic development was initially tested in 2012, where it was established that the cycle of real stock prices on the JSE leads the cycle of real economic activity (Auret & Golding, 2012). Sayed et al. (2017) then revealed strong evidence of the JSE being a leading indicator of economic activity. The findings of this study were for the period of March 1998 to December 2016. This study aims to corroborate these findings, while incorporating an additional year of data.

2.1.2. Empirical Findings of No Such Relationship

In light of the above widespread research that shows a relationship between stock returns and economic development, it is worth highlighting that not all studies arrive at the same conclusion. Even though they are in the minority, there are studies that counter the argument and suggest that the stock market has no predictive characteristic of economic activity.

Contradictory to the abovementioned Comincioli (1996), many developed markets have been found to have no predictive relationship (or Granger causality) of real macro-economic variables. Johann Burgstaller (2002) confirmed this and concluded that stock returns do not have predictive capabilities for growth rates in industrial production, a variable this study uses to represent economic activity. Minsoo (2006) found that there is no evidence that the New Zealand Stock Index is a leading indicator for changes in macroeconomic variables (including GDP), however it does conclude that a reason for this may be the small size of the New Zealand market. It suggests that the small size of the market results in a low impact of the capital markets on the economy as a whole. Men & Li (2006) asked the research question, 'Should the national economy lead the stock market or the other way round?'. The result of the empirical analysis shows that there is no co-integration relationship between the stock market index and the national economy in China. Notably, it also establishes that there is no Granger causal relationship between stock index yield and the national economy growth rate (GDP). These unexpected results, however, was explained by the inconsistent composition of the Chinese GDP and the Chinese market. Barro (1990), who found there to be "strong evidence of stock prices having substantial explanatory power for subsequent U.S. investment" also showed in the same study that the stock market was incorrect at predicting three recessions that did not occur in the United States in 1963, 1967 and 1978 – indicating the potential error in its predictive ability.

Some reasons have been speculated as to why there could be no significant causal relationship between the stock market and economic activity. Pearce (1983) pointed out that the stock market, being made up of future looking prices, can build in erroneous expectations, which therefore can damage its ability to predict. In addition, the stock market is questioned to be a valuable predictor because of the influence of investors' expectations, which are argued to contain inherent human error, allowing stock prices to diverge from what is the true economy (Brad Comincioli, 1996).

Different methodologies can also effect the statistical outcome of such causal tests, and therefore, differing conclusions. Regardless of what the reason for no relationship may be, however, it is clear that there is some contradictory evidence of the relationship between the stock returns and economic activity. As a result, it becomes valuable to perform further testing of this relationship in South Africa, where research has been light to date.

2.2. Financial Development and Economic Activity

2.2.1. Financial Development Defined

Financial development is broad and is made up of a variety of factors in a specific country. It is affected by many factors, including a country's stage of economic development as well as its legal and institutional frameworks (Peia & Roszbach, 2015). As a result of the inherent complexity that makes up the financial system as a whole, it is very difficult to use a single measure to represent it, and thus it becomes more appropriate to focus on an aspect of financial development, in order to draw some specific conclusions.

The key focus for this study, regarding financial development, will be the banking sector development, represented by the total level of credit (or total assets) in the banking sector in South Africa. The choice of total credit levels in the banking sector is consistent with Peia (2015) who made use of bank credit to the private sector as the banking sector development measure. Ndako (2010) also made use of a similar variable for financial development when it tested for causality between financial development and economic growth using bank credit to the private sector. Other studies have made use of different banking development measures such as the country's broad money supply, claims on private sectors, domestic credit provided by banking sector, domestic credit to the private sector, or a composite index (using a make-up of banking sector indicators) (Pradhan, Arvin, Hall, & Bahmani, 2014).

This study, however, includes public lending as it is a key source of economic spending within South Africa, even though it is a minority of the total lending pool.

2.2.2. Empirical Findings of an Existing Relationship

The relationship between a country's financial development and its economic development is key but also complex and therefore it has been extensively explored. Levine (1997) managed to put it succinctly to state that the multitude of theoretical reasoning and empirical evidence suggests that a positive, first-order relationship exists between financial development and economic growth. By examining the research, it is difficult to dissociate financial development and the growth process and so it is well recognized that financial development is key for economic growth (Calderón & Liu, 2003).

Several theories have been developed to encapsulate the relationship of financial development and economic activity. The theories, which mainly stem from Patrick (1966), also assist in pointing out the distinct differences in research findings regarding causality in the relationship.

The first of these theories is that of the "supply-leading hypothesis" which supposes a causal relationship from financial development to economic growth. This theory means that an intentional creation of a financial market would increase the supply of financial services and therefore precede economic growth (Calderón & Liu, 2003). Schumpeter (1934) authored this theory explaining how financial intermediaries play a pivotal role in output growth by means of savings and then productive investments. In more recent years King and Levine (1993) proved that better financial systems improve the probability of successful innovation and thereby accelerate economic growth while Levine et al. (2002) added that development of financial intermediaries exerts a large causal impact on growth. Calderón and Liu (2003) added a characteristic to this relationship by examining the direction of causality between financial development and economic growth and it concluded that financial development generally leads to economic growth. Greenwood and Smith (1997), Christopoulos and Tsionas (2004), Loayza et al. (2006) and Peia and Roszbach (2015), have all also supported the supply-leading hypothesis over the years. This paper aims conclude on the same causality tests between financial development and economic growth in the South African context.

The second of these theories is that of the "demand-following hypothesis", which suggests an opposing causal relationship from economic growth to financial development. In this case, an increased demand for financial services in a growing economy would prompt growth in the financial sector. Robinson (1952) was the first to argue that financial development simply follows economic growth (which is generated elsewhere), but has been supported over the years by Gurley and Shaw (1967), Goldsmith (1969) and Jung (1986). Pradhan et al. (2013) developed keen observations of Bangladesh, Bhutan, Pakistan, China, Hong Kong, Japan, Indonesia, Malaysia, South Asia, and East Asia all indicating that economic growth leads to financial development, supporting the demand-supply hypothesis. Interestingly, findings like that of Blackburn and Hung (1998) as well as Calderón and Liu (2003), establish a positive, two-way causal relationship between growth and financial development – highlighting the possible interactions of the two theories.

Patrick (1966) also indicates a third theory, the "stage of development" hypothesis, which details a limitation to the supply-leading hypothesis above. It postulates that, in the early stages of economic development, financial development can induce capital formation in the industry. This early and innovative financial development would provide new opportunities for savers and investors and thus stimulate economic activity and meet the theory of the supply-leading hypothesis. However, it also finds that these supply-leading characteristics of financial development weaken over time. This is supported by the findings of Cecchetti and Kharroubi (2012) which indicated that the level of financial development is good for economic growth up to a point, after which it becomes a drag. Law (2014) additionally highlighted this theory by presenting a threshold effect in the finance–growth relationship. It finds that the level of financial development is beneficial to growth only up to a certain threshold, beyond which, any further development of finance has a tendency to adversely affect growth. Rioja and Valev (2004) expanded on other studies to show that finance may have a different effect on growth in different countries, time periods or stages of development (Levine et al., 2000) (De Gregorio & Guidotti, 1995) (Demetriades & Hussein, 1996).

This study will specifically focus on the causal relationship of the financial sector development and economic growth in the South African context where the financial sector is mature, being the most financially advanced economy in the SADC (Southern African Development Community) (Bara & Le Roux, 2017). It will therefore be noted whether the causal relationship of financial development and economic activity falls into one of these theories, given its stage of completion.

For the most part, the empirical evidence has demonstrated that there is a positive long-run association between the indicators of financial development and economic growth. Overall, such papers would suggest that a strong financial system allows room for economic growth, and is hence, consistent with the proposition of "more finance, more growth" (Law & Singh, 2014) as well as the supply-leading hypothesis.

2.2.3. Empirical Findings of No Such Relationship

Regarding causality, many similar studies have occurred for both developing and developed countries. Through most of these studies, the existence of a causal relationship from financial development to economic growth has been confirmed. However, there are a few cases where there is no evidence of causality from financial development to economic growth. Lucas (1988) proposed that financial matters were over-stressed in the growth forecast, while Eng and Habibullah (2011) find indications of non-causality between the financial development and economic growth in some of the areas of Africa, Asia, Europe and the Western Hemisphere. Mukhopadhyay et al. (2011) investigates the causal relationship between financial development and economic growth for the period between 1979 and 2009 to find that Malaysia's financial development does not seem to cause economic growth. Pradhan et al. (2013) found that only India, out of fifteen Asian countries, provided an indication of a causal relationship from financial development to economic growth, showing that the norm in that case was the absence of a causal relationship.

To add weight to the contrary evidence of the finance-growth relationship, Rati (1999) also argued that the results pertaining to the finance-growth nexus are, in the best case, uncertain and ambiguous. The statistical findings are indicative of a negligible, or perhaps negative, association between financial development and growth of real GDP per capita. Finally, Khan and Senhadji (2003) also demonstrate that certain banking development indicators become statistically insignificant through the use of panel data.

Results such as these, which differ from the mean findings in this area of study, confirm the importance of acknowledging the uniqueness of the country's economic position when it is used as a destination to explore the role of finance in economic development. This important caveat was highlighted by Rioja and Valev (2004) who showed that the link between finance and growth depends on the stage of economic development. It clarified that highly and low developed economies maintain a weak link between the two variables, whereas for developing countries, financial development exercises a stronger influence on growth (Peia & Roszbach, 2015).

Additionally, Levine (2002) puts forth possible reasons to account for the fact that banking development may actually hinder growth, and thus negative relationship between finance and growth. First, banks may possess huge influence over firms, which may manifest itself in negative ways. This could manifest itself in banks extracting greater profits than expected from the firms, where their future growth may be hindered. Secondly, banks are seen to have an inherent bias toward prudence, which may mean that banking development impedes corporate innovation and growth.

2.3. Empirical Research's Impact on This Study

The research on the stock market and banking sector's relationships with economic activity is vast, but there remains the need to accurately conclude on these relationships in the South African context.

This study aims to resolve which type of relationship, if any, the South African stock market has with its economic activity. The bend of existing research of developing markets suggests that the 'wealth effect' holds, where overall high share portfolio level produces higher consumer spending and thus increased economic activity.

This relationship, of stock market changes and economic growth in South Africa, needs to then be compared to the relationship of banking sector development and economic activity. One wants to particularly conclude on how the finance-growth nexus holds up in the South African context if one utilises the level of banking assets as a means to represent financial development. Additionally, one looks to settle whether there a causal relationship from financial development to economic growth, which would support the supply-leading hypothesis.

The literature seems to favour an outcome which indicates that South Africa, being a developing country, has a positive relationship between stock market changes as well as financial development to economic activity. However, as we have seen, this is merely an expectation until it is proven.

The most relevant work on causal relationships of economic activity for this paper are the South African published papers by Auret & Golding (2012), Sayed et al. (2017) and the study on Malaysian by Har et al. (2009). Auret & Golding (2012) provide the first findings of the relationship between stock markets and economic activity in South Africa by employing a regression analysis with and autoregressive equation, and premise the study on the existence of trends and non-stationarity of the time-series data. Sayed et al. (2017) provide a different analysis with the use of Granger-causality testing after confirming the stationarity of the data. Har et al. (2009) similarly test for the time series' stationarity and Granger-causality in the Malaysian context.

Auret & Golding (2012) find limitations in the autoregressive model that is used in its analysis. The model's limitation scopes Sayed et al. (2017) to provide a variation to the study through the use of Granger-causality testing, which Har et al. (2009), and now this study, also follows. As much as this study tracks the approach of Sayed et al. (2017) and Har et al. (2009), it does make some additions and adjustments. Firstly, the stationarity testing of the variables is further emphasised. This is done because the Granger-causality testing can only hold for stationary variables, which means that the conclusions on the stationarity of the data is key. This paper finds the stationarity testing of Sayed et al. (2017) and Har et al. (2009) light, which casts potential doubt over the conclusiveness of the respective Granger-causality findings. Linked to this, this paper also notes that Sayed et al. (2017) performs Granger-causality tests with the use of GDP as its resulting economic indicator, however it is not explicit in asserting GDP's stationarity post differencing (see chapter 3 for the methodology regarding differencing data for stationarity transformation). Thus, the added emphasis of this paper on stationarity testing results in it adding two more stationarity tests (the Kwiatkowski-Phillips-Schmidt-Shin test and Lo-MacKinlay test) to its methodology in order to form a more robust assessment of each variables' stationarity before assessing and concluding on any causal relationships. It will also focus on empirically indicating GDP's stationarity status. The other adjustment of this paper is the interpretation of the Index of Industrial Production (IIP), which this paper sees as a volume-based index, which is made up of seasonally adjusted volumes of production. Because volumes are not affected by prices, this paper finds no justification to deflate the series to convert it to a "real" time series, which is the preferred approach taken by Sayed et al. (2017).

2.4. Note on Correlation of Dependent Variables

As mentioned above, this paper assesses the predictive nature of the stock market and the banking sector changes for economic activity. In order to warrant the independent testing of the predictability of both variables, the correlation between the respective variables needs to be assessed. Due to the absence of clear strong correlation between the stock market variables and the banking sector variable, the testing of both is warranted. Below is the summary of the correlation between the stock market variables (ALSI, INDI, FINI, RESI) and the banking sector variable (BANKDEV).

Correlation of Independent Variables Used in Testing

Monthly Year on Year Correlation of Variables' Movements

	ALSI	INDI	RESI	FINI
BANKDEV	0.44	0.13	0.48	0.12

	ALSIR	INDIR	RESIR	FINIR
R BANKDEV	0.58	0.32	0.53	0.33

Quarterly Year on Year Correlation of Variables' Movements

	ALSI	INDI	RESI	FINI
BANKDEV	0.45	0.12	0.50	0.11

	ALSIR	INDIR	RESIR	FINIR
R BANKDEV	0.58	0.31	0.56	0.33

It is noted that the correlation is higher between the ALSI and RESI indicators, which may need to be considered in the results interpretation.

Chapter 3: Data and Methods

3.1. Data

The goal of this study is to ascertain whether or not the changes in South African bank institutions' assets and/or the JSE share prices lead changes in economic activity in South Africa over the period from 1 February 1998 to 31 October 2017. The period selected for testing is based on the maximum length of time where all the data is available and comparable, noting that February 1998 is the earliest point in time when all variables are available.

The two variables used to proxy for economic activity in South Africa are GDP (Gross Domestic Product) and IIP (Index of Industrial Production). Even though most studies generally make use of either GDP or IIP as an economic indicator, this study follows Fama (1981) as well as Auret and Golding (2012) where the test was conducted in the South African context with the use of both variables for the first time.

GDP and IIP data is obtained from the SARB. Variables representative of economic activity are defined as follows:

i. GDP: Nominal year on year (YoY) growth rate of South Africa's GDP using quarterly figures.
ii. R GDP: YoY growth rate of South Africa's real GDP using quarterly figures.
iii. IIP: YoY percentage change on South Africa's IIP using monthly figures. (IIP is a volume based index and therefore there is no 'nominal' or 'real' variation.)

The independent variables of this study represent the banking sector development as well as the stock market performance. The banking sector variable will be defined by the changes in the total assets of South African banking institutions, obtained from the SARB (defined as BANKDEV). The inflation adjusted variation of this variable will be defined as *RBANKDEV*.

Calderón & Liu (2003) indicate that financial development is acceptably defined as the improvement of quantity, quality and efficiency of financial intermediary services. That definition, however, includes a number of processes and variables that cannot be easily captured by a measure. As explained in Chapter 2.2.1, this study has used the total assets of South African banking institutions as its proxy which coincides with similar variables like broad money or total credit to private sector (Levine et al., 2000).

The stock market performance is most easily represented by the relevant indices. The main index for the JSE (the main South African securities exchange) is the All Share Index (ALSI). However, research has argued that the ALSI is not mean-variance efficient and therefore, on its own, may not be an appropriate market proxy. As a result, in addition to the ALSI proxy, the study will incorporate the three sector indices of the JSE, following a similar methodology to Sayed et. al (2017). These monthly stock market variables will therefore be defined as follows:

i. ALSI: YoY percentage change on the JSE All-Share Index (J203) using nominal share price data.
ii. ALSIR: Nominal J203 share price data is first deflated using CPI, then the YoY percentage change is calculated to construct the series in real terms.
iii. INDI: YoY percentage change on the Industrial Index (J211) using nominal share price data.
iv. INDIR: Nominal J211 share price data is first deflated using CPI, then YoY percentage change is calculated to construct the series in real terms.
v. FINI: YoY percentage change on the Financial Index (J212) using nominal share price data.
vi. FINIR: Nominal J212 share price data is first deflated using CPI, then YoY percentage change is calculated to construct the series in real terms.
vii. RESI: YoY percentage change on the Resources Index (J210) using nominal share price data.
viii. RESIR: Nominal J210 share price data is first deflated using CPI, then YoY percentage change is calculated to construct the series in real terms.

The period for this analysis (1 February 1998 to 31 October 2017) results in 225 monthly, year on year return observations (with respect to all variables except GDP and real GDP) and 75 quarterly, year on year return observations (all variables included) available for testing.

3.2. Methods

3.2.1. Stationarity Testing

Before a causal relationship between the variables can be tested, each variable data set is required to be tested for stationarity. Each data set is tested for stationarity. This includes the quarterly data for GDP and R GDP as well as the monthly and quarterly data sets for IIP, BANKDEV, RBANKDEV ALSI, ALSIR, INDI, INDIR, FINI, FINIR, RESI and RESIR.

Several tests are used in order to gain greater assurance of the stationarity of the variables. These three tests follow below:

Augmented Dickey-Fuller test (unit root)

First, the Augmented Dickey-Fuller (ADF) test is used to assess the stationarity of the variables in this series. The methodology comes from the work of Dickey and Fuller (1979) where the augmented Dickey Fuller (ADF) test originated. This ADF test is the first test which established whether time series data contained a unit root and thus implying non-stationary and is widely accepted as the most prominent test for unit root.

The null hypothesis of the ADF test is that a time-series, y(t), has a unit root. The alternative of that hypothesis is that y(t) is generated by a stationary process. In this study the ADF test is performed with and without a trend term for completeness[1]. The ADF test runs for a model that makes use of an 'optimal' lag length obtained from the minimum Schwarz information criterion (SIC)[2], which has been prominently used as an optional optimal lag length for research over the years (Liew, 2004).

The method to obtain the lag length using the minimum SIC requires the use of the modified Dicky Fuller (DF) test which is also used to test the stationarity of the variables. The modified DF test is essentially the same as the ADF test except that the data is transformed via a generalised least squares (GLS) regression before performing the test (Cheung & Lai, 1995). The modified DF test runs for the series of models that include 1 to 'k' lags of the first-differenced, detrended variable, where the max of 'k' is set by the method described in Schwert (1989)[3]. It is within this range of lags that the optimal lag length is established with the use of the minimum SIC. This is the methodology followed for the ADF testing of this study.

Kwiatkowski-Phillips-Schmidt-Shin test

The Kwiatkowski, Phillips, Schmidt, Shin (KPSS) test looks to prove the stationarity of a time series. This test differs from the above ADF and DF-GLS by having a null hypothesis of stationarity (Kwiatkowski, Phillips, Schmidt, & Shin, 1992).

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[1] Calculated with: $\Delta y_t = \alpha + \beta t + \gamma y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1} \Delta y_{t-p+1} + \varepsilon_1$,

[2] Calculated with: $SIC = ln(r\widehat{ms}e^2) + (k+1)\frac{\ln(T-k_{max})}{(T-k_{max})}$,

w $r\widehat{ms}e^2 = \frac{1}{(T-k_{max})}\sum_{t=k_{max}+1}^{T} \hat{e}_t^2$.

[3] This formula is $\mathrm{kmax} = \mathrm{floor}[12\{(\mathrm{T}+1)/100\}^{0.25}]$.

While the ADF statistic tests to confirm the unit root null hypothesis, the KPSS statistic tests to confirm the reverse, being the trend stationarity null hypothesis against the unit root alternative. Given the different specifications of the null and alternative, the KPSS test can provide useful additional information regarding the unit root's persistence within the data set (Cheung & Ng, 1998).

The KPSS test is conducted under the null of firstly trend stationarity, and then level stationarity. This test is often used in conjunction with DF-GLS or ADF tests to investigate the possibility that a series is fractionally integrated to add robustness to the stationarity test (StataCorp, 2017).

The max lag length is calculated similarly to the DF-GLS test above using the methodology of Schwert (1989) and the test is performed for each lag up to the maximum lag length.

Lo-MacKinlay test (unit root)

The Lo-Mackinlay test computes an overlapping variance-ratio (VR) test on a time series – i.e. testing the consistency of the variance from the mean in a time series. This is done to assess non-stationarity in a time series that is in level form. An example of the application of this test could be to test how stock returns vary around a constant mean, in which case, the null hypothesis would be that the log stock price series is 'a random walk with drift' (i.e. has a unit root and is non-stationary).

For the Lo-Mackinlay test, a time series that contains a unit root will see its variance grow linearly over time. Therefore, k periods multiplied by the variance from period 1 should be equal to the variance in the kth period. In the event of a deviation of the VR statistic from a ratio equal to one, this would indicate a departure from the unit root hypothesis and therefore allow a rejection of the hypothesis and thus a rejection of non-stationarity. (StataCorp, 2017).

The standard sampling intervals (q) for the test of of 2, 4, 8 and 16 (months or quarters depending on the variable) are used based on Box-Steffensmeier et al. (2014) and Sayed et al. (2017).

3.2.2. Why All Three Stationarity Tests?

The above three tests are all used in order to gain further assurance of the stationarity of the data sets. This is because finding stationarity through the DF-GLS test is less meaningful than finding stationarity to be true across the DF-GLS, KPSS and Lo-Mackinlay tests. With each additional stationarity test performed on a time series data (which confirms stationarity), one gains more confidence that the data is stationary because each additional test is confirming the stationarity nature from a different angle, thus building a more robust analysis. Where a specific data set is found to be non-stationary in any of the three tests, data transformation options will be explored by means of log linear models as well as differencing (to no more than the second degree, which follows the methodology of Sayed et al. (2017) where first differencing was employed on the GDP data to transform it to be stationary in nature. In this study, where non-stationarity has been picked up in the testing, the log-linear model will be applied to the data and then re-tested accordingly (Huang, Wu, Qu, Long, & Shen, 2003). If non-stationarity persists post log-linear model attempts, the data will be differenced up to the second degree.

The (transformed) data is tested across the three tests to find assurance of stationarity before being tested for Granger-causality.

3.2.3. Granger-causality Tests

The Granger test of 1969 (Granger, 1969) has the unique ability to indicate predictive causality within a relationship between two time series'. I.e. Time series Y is said to be caused by time series X, where the historic values of X are found to provide statistically significant information about the future values of Y. A time series can 'Granger-cause' another time series if it has the predictive power to forecast its incremental changes (Gelper & Croux, 2007).

Pairwise Granger-causality tests are conducted between different combinations of variables. Firstly, between the quarterly, year on year percentage change in GDP data, and the quarterly year on year percentage change for each of the four stock indices as defined. Secondly, between the same (quarterly) Year on year percentage change in GDP, and the quarterly year on year percentage change in South African bank asset levels. Thereafter, pairwise Granger-causality tests are conducted between monthly, year on year percentage change in IIP data, and the monthly year on year percentage change for each of the four stock indices as defined. The final combination of variables for Granger-causality testing is between the monthly year on year percentage change in IIP, and the monthly year on year percentage change in South African bank asset levels.

There are several distinctions of causality that will be in the Granger-causality tests for the given relationships:

1. Unidirectional Granger-causality from the stock market variables (ALSI, INDI, FINI, RESI) and the banking sector variable (BANKDEV), to the macroeconomic variables (GDP, IIP). In the case of unidirectional Granger-causality, the share prices and the banking sector development lead economic activity only.

2. Reverse Granger-causality from the macroeconomic variables to the stock market and banking sector variables. In the case of reverse Granger-causality, the share prices and the banking sector development do not lead economic activity.

3. Bidirectional or feedback causality. In the case of bidirectional causality, causality is observed in both directions between the share prices and the banking sector development and economic activity.

4. Independence between all the variables. In the case of independence of the variables, there is no Granger-causality observed in either direction.

The choice of lag lengths for the Granger-causality testing is guided by Box-Steffensmeieret al. (2014) which finds several approaches to the selection of the lag length. One of these approaches is to cover the full cycle of the data. In this study's case the full cycle of share prices, banking development is quite subjective but six lags for quarterly data is more than appropriate. Six lags is also used for monthly data as it seems to cover the full data cycle of semi-annual periods and follows the methodology of Sayed et al. (2017).

An example of the model specifications for the extensive Granger testing will take the form of the following:

$$GDP_t = \alpha_0 + \alpha_1 GDP_{t-1} + \dots + \alpha_l GDP_{t-l} + \beta_1 ALSI_{t-1} + \dots + \beta_l ALSI_{t-l} + \mu_t$$

The above formula would be a Granger test regarding the causal relationship between the independent variable (ALSI) and the dependent variable (GDP). In this case, the formula specifically represents a test of whether an ALSI index change (stock market movement) Granger-causes a change to GDP (economic activity). The order of causality is specific from ALSI to GDP.

In Chapter 4, sixty independent Granger tests performed to address all of the possible Granger-causality relationships as mentioned in points 1 – 4 above.

Chapter 4: Results and Analysis

4.1. Stationarity Tests

The data sets are tested using each of the three stationarity tests, being AFS, KPSS and Lo-MacKinlay. Every data set is systematically tested with each test type, and where a test indicates that the time series proves non-stationarity, the respective data set is transformed and retested. As already mentioned, a systematic and consistent process is applied to transform the data in the case of non-stationary. First, by applying the log-linear model, and second by applying differencing. In the transformation process for this study it is mainly found that data which initially show stationarity at a prior stage of the data transformation process, does not contradict that finding at a later stage in the transformation process. For example, if a data set was found to be stationary for a given test after log-linear transformation, it also shows the same degree of stationarity for that test after differencing. (This is applicable unless otherwise stated in the results). The reason data sets may require further transformation (even though at an earlier stage of the transformation process stationarity is shown) is because one of the other stationarity tests fails to prove stationarity for the data at that stage of its transformation. The goal is to show stationarity across the three tests with the use of a consistent (transformed) data set.

4.1.1. Nominal Quarterly Data.

Table 1 summarises the findings of all the nominal quarterly data stationarity testing.

Table 1: Summary of Stationarity Testing (Nominal Quarterly)

Variable	SIC lags suggested	ADF intercept only	*P Value*	ADF intercept & trend	*P Value*	KPSS trend stationary	KPSS level stationary	Lo-MacKinlay	*Respective intervals(q)*
ALSI	**1**	✓	**0.0012*****	✓	**0.0036*****	✓	✓	✓	**2;4**
INDI	6	✓	0.0629*	✗	0.1481	✗	✓	✗	-
lnINDI	6	✓	0.065*	✗	0.1169	✓	✗	✓	2;4
D.INDI	**5**	✓	**0.0011*****	✓	**0.0085*****	✓	✓	✓	**2;4;8**
RESI	4	✗	0.1777	✗	0.1247	✓	✓	✓	2;4
lnRESI	1	✓	0.0028***	✓	0.0024***	✓	✗	✓	4
D.RESI	**1**	✓	**<0.0001*****	✓	**0.0001*****	✓	✓	✓	**2;4;8**
FINI	4	✓	0.0365**	✗	0.1446	✗	✓	✗	-
lnFINI	4	✓	0.031**	✗	0.129	✗	✓	✓	4
D.FINI	**3**	✓	**<0.0001*****	✓	**0.0012*****	✓	✓	✓	**2;4;8**
BankDev	2	✓	0.55	✓	0.0714*	✗	✗	✓	2;4;8;16
lnBankDev	2	✓	0.551	✓	0.0716*	✗	✗	✓	4;8;16
D.BankDev	**3**	✓	**<0.0001*****	✓	**0.0001*****	✓	✓	✓	**2;4;8**
IIP	4	✓	0.0402**	✗	0.1008	✓	✓	✗	-
lnIIP	4	✓	0.0464**	✗	0.1199	✓	✓	✗	-
D.IIP	**3**	✓	**<0.0001*****	✓	**<0.0001*****	✓	✓	✓	**2;4;8**
GDP	4	✗	0.6014	✗	0.1036	✗	✗	✗	-
lnGDP	4	✗	0.6054	✗	0.1056	✗	✗	✗	-
D.GDP	**3**	✓	**<0.0001*****	✓	**<0.0001*****	✓	✓	✓	**2;4;8**

✓	Stationarity nature concluded for corresponding data set
✗	Non-stationarity nature concluded for corresponding data set
***	Denotes significance at the 1% level.
**	Denotes significance at the 5% level.
*	Denotes significance at the 10% level.

Augmented Dickey-Fuller test (unit root)

The tests with only a constant and no trend in the equation, reveal that ALSI, INDI, FINI, BANKDEV and IIP all exhibit stationarity by rejecting the unit root hypothesis, while RESI and GDP contain a unit root. The RESI data transformed by log linear (log-linear transformation is indicated by the prefix 'ln' of lnRESI) is found to indicate stationarity by rejecting the unit root, while GDP requires differencing (differencing is indicated by the prefix 'D' in D.GDP) to reject the unit root hypothesis and reveal stationarity.

The tests appear sensitive to the inclusion of a trend as they yield different results. In this case only ALSI and BANKDEV are found to not contain a unit root without any transformation, while INDI, RESI, FINI, IIP and GDP all fail to reject the unit root test and therefore indicate non-stationarity. After transforming these data sets, it is found that the difference of INDI (D.INDI), FINI (D.FINI), IIP (D.IIP) and GDP (D.GDP) all reject the unit root test, while the log-linear of RESI (lnRESI) is found to reject the unit root hypothesis.

It is noted that part of the methodology of ADF test, systematically differences the data set being tested. It does this in order to control for serial correlation. However, the ADF test hypotheses and concludes on the original data being tested, and not the differenced data that forms part of its methodology. The hypothesis rejection of the ADF test is established through the examination of the p value.

The summary of all the stationarity tests is provided at the end of this section in Tables 1 – 4, while some statistical details on the KPSS and Lo-MacKinlay tests are provided in the Appendix. Table 1 summarises the nominal quarterly data stationarity testing.

Kwiatkowski-Phillips-Schmidt-Shin test

The KPSS test on the null of trend stationarity finds ALSI, RESI and IIP to be stationary in nature, while INDI, FINI, BANKDEV and GDP reject the stationary hypothesis. Stationarity is confirmed for all the variables after they are differenced (D.INDI, D.FINI, D.BANKDEV, and D.GDP) after the log linear model application fails to transform the data in each case.

The KPSS test on the null of level stationarity establishes different outcomes where ALSI, INDI, RESI, FINI and IIP all confirm the stationarity hypothesis. As is the case in the trend tests, these variables requires first differencing of the other variable data (D.BANKDEV and D.GDP) to arrive at stationarity being confirmed.

The hypothesis is confirmed by observing the test statistic being less than the critical values at certain confidence levels – indicated in the Appendix.

Lo-MacKinlay test (unit root)

The Lo-MacKinlay test's hypothesis is that the data level is a random walk (and contains a unit root). This test begins with variable data which has already proven to be stationary in the above two tests. I.e. where data previously required differencing to prove stationarity, the differenced data is used at the start for Lo-MacKinlay testing.

The outcome of this testing sees ASLI rejecting then hypothesis with sampling intervals (q) up to 4. After transforming data in line with previous tests, it is found that D.FINI rejects the hypothesis at the 99% confidence level with sampling intervals (q) up to 8. D.INDI, D.IIP and D.GDP establish proof to reject the unit root hypothesis with sampling intervals (q) up to 8 in each case.

The hypothesis rejection of the Lo-MacKinlay test is established through the examination of the p values, as provided in the Appendix.

4.1.2. Real Quarterly Data

Table 2 summarises the findings of all the real quarterly data stationarity testing.

Table 2: Summary of Stationarity Testing (Real Quarterly)

Variable	SIC lags suggested	ADF intercept only	*P Value*	ADF intercept & trend	*P Value*	KPSS trend stationary	KPSS level stationary	Lo-MacKinlay	*Respective intervals(q)*
ALSIR	**1**	✓	**0.001*** **	✓	**0.0032*** **	✓	✓	✓	**2;4**
INDIR	6	✓	0.0533*	✗	0.1382	✗	✓	✓	4
lnINDI	6	✓	0.065*	✗	0.1169	✗	✓	✓	2;4
D.INDIR	**5**	✓	**0.0015*** **	✓	**0.0115** **	✓	✓	✓	**2,4;8**
RESIR	4	✗	0.1761	✗	0.12	✓	✗	✓	2;4
lnRESIR	1	✓	0.0024***	✓	0.002***	✓	✗	✓	2;4
D.RESIR	**1**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2,4;8**
FINIR	4	✓	0.0333**	✗	0.1336	✗	✓	✓	4
lnFINIR	4	✓	0.0294**	✗	0.1227	✗	✓	✓	4
D.FINIR	**3**	✓	**0.0002*** **	✓	**0.0015*** **	✓	✓	✓	**2,4;8**
RBankDev	1	✗	0.1461	✗	0.1842	✗	✗	✓	2;4;8;16
lnRBankDev	1	✗	0.1386	✗	0.1756	✗	✗	✓	2;4;8;16
D.RBankDev	**3**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2,4;8**
RGDP	1	✓	0.0261**	✓	0.0122**	✗	✗	✓	2
lnRGDP	1	✓	0.0231**	✓	0.0107**	✗	✗	✓	2
D.RGDP	1	✓	0.0001***	✓	0.0011***	✓	✓	✗	-
D2.RGDP	**1**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2,4;8**

✓ Stationarity nature concluded for corresponding data set
✗ Non-stationarity nature concluded for corresponding data set
*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

Augmented Dickey-Fuller test (unit root)

For the real quarterly data, the ADF tests with a constant and no trend in the equation, show that ALSIR rejects the unit root hypothesis. FINIR and RGDP reject it at the 95% level, and then, at the 99% confidence level for the differenced data (D.FINIR and D.RGDP) post transformation. INDIR indicates stationarity at the 90% confidence level but again rejects the hypothesis of a unit root at the 99% confidence level when the data was differenced (D.INDIR). RESIR and RBANKDEV are unable to reject the hypothesis outright. RBANKDEV requires differencing to reject the hypothesis, but RESIR rejects the unit root test at the 99% confidence level after the log-linear model transformation (lnRESIR).

The tests seem sensitive to the inclusion of a trend in the case of the real data as they produce dissimilar results. ALSIR again rejects the hypothesis outright without the need for transformation and RGDP rejects it at the 95% level, but at the 99% confidence level where the data is differenced (D.RGDP). However, INDIR, RESIR, FINIR and RBANKDEV are all unable to reject the unit root. After similar transformation mentioned in the 'no trend' testing, lnRESIR, D. FINIR and D.RBANKDEV all reject the unit root test to indicate stationarity, while D.INDIR rejects the unit root at the 95% level.

Kwiatkowski-Phillips-Schmidt-Shin test

The KPSS test on the null of trend stationarity for the real quarterly data finds ALSIR and RESIR to be stationary in nature, while INDIR, FINIR, RBANKDEV and RGDP reject the stationary hypothesis. Stationarity is confirmed for all of the variables after they are differenced (D.INDIR, D.FINIR, D.RBANKDEV and D.RGDP) and the tests confirm t statistics of less than the critical values at the highest confidence level.

The KPSS test on the null of level stationarity establishes some different outcomes where ALSIR, INDIR and FINIR and all confirm the stationarity hypothesis. The remaining variables all require differencing to prove the same. D.RESIR, D.RBANKDEV and D.RGDP do not reject the hypothesis of stationarity.

Lo-MacKinlay test (unit root)

The outcome of the test to see if the real quarterly data level is a random walk (with a unit root). Again, this test acknowledges the need to test the transformed data from the other two tests.

ALSIR did not need to be transformed in any other test, however INDIR, RESIR, FINIR, RGDP and RBANKDEV were all required to be differenced and so are tested here based on the same transformation. D.INDIR, D.RESIR, D.FINIR and D.RBANKDEV are found to reject the random walk hypothesis at varying sample intervals, while RGDP, which initially indicated stationarity for Lo-Mackinlay before any transformation, is not able to reject the random walk hypothesis after being logged or after applying first differencing principles. (This is the one instance in the testing where the stationarity nature of the data has changed from initially indicating stationary before transformation to then showing no indication after the systematic transformation process explained above). In order to establish stationarity in the RGDP variable, the data is second differenced.

The Lo-MacKinlay test on the second differenced data (D2.RGDP) finds the random walk hypothesis rejected for intervals (q) 2, 4 and 8, along with the same findings for D.INDIR, D.RESIR, D.FINIR and D.RBANKDEV. ALSIR also rejected the unit root test for up to 4 quarters (q).

4.1.3. Nominal Monthly Data

Table 3 summarises the findings of all the nominal monthly data stationarity testing.

Table 3: Summary of Stationarity Testing (Nominal Monthly)

Variable	SIC lags suggested	ADF intercept only	*P Value*	ADF intercept & trend	*P Value*	KPSS trend stationary	KPSS level stationary	Lo-MacKinlay	*Respective intervals(q)*
ALSI	1	✓	0.0045***	✓	0.0161**	✗	✗	✓	2;4;8
lnALSRI	1	✓	0.0048***	✓	0.0196**	✗	✗	✓	2;4;8
D.ALSI	**1**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2;4;8;16**
INDI	1	✓	0.0255**	✗	0.1068	✗	✗	✗	-
lnINDI	12	✗	0.1649	✗	0.3465	✗	✗	✗	-
D.INDI	**11**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2;4;8;16**
RESI	12	✗	0.1507	✗	0.1613	✗	✗	✗	-
lnRESI	12	✗	0.1512	✗	0.1824	✗	✗	✗	-
D.RESI	**11**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2;4;8;16**
FINI	1	✓	0.009***	✓	0.497	✗	✗	✗	-
lnFINI	1	✓	0.0053***	✓	0.338	✗	✗	✗	-
D.FINI	**11**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2;4;8;16**
BankDev	12	✗	0.373	✗	0.5297	✗	✗	✓	8;16
lnBankDev	12	✗	0.377	✗	0.5405	✗	✗	✓	8;16
D.BankDev	**11**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2;4;8;16**
IIP	1	✓	0.0019***	✓	0.0081***	✗	✗	✓	2;4;8;16
lnIIP	1	✓	0.0026***	✓	0.0114**	✗	✗	✓	2;4;8;16
D.IIP	**1**	✓	**<0.0001*** **	✓	**<0.0001*** **	✓	✓	✓	**2;4;8;16**

✓ Stationarity nature concluded for corresponding data set
✗ Non-stationarity nature concluded for corresponding data set
*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

Augmented Dickey-Fuller test (unit root)

The ADF tests for the nominal monthly data with only a constant and no trend in the equation, reveal that ALSI, INDI, FINI and IIP all reject the unit root hypothesis, while RESI and BANKDEV confirm the data contains a unit root. The RESI and BANKDEV data require differencing (D.RESI, D.BANKDEV) before being able to reject the unit root hypothesis and demonstrate stationarity.

The inclusion of a trend in the ADF test delivers slightly different outcomes. In this case only ALSI and IIP are found to not contain a unit root without any transformation at the highest confidence levels, while the test for FINI rejects the unit root at the 90% confidence level. The data requires transformation through differencing, which allows the unit root to be rejected for D.INDI, D.RESI and D.BANKDEV. D.FINI data is also found to reject the hypothesis at the highest confidence level.

Kwiatkowski-Phillips-Schmidt-Shin test

The KPSS test on the null hypothesis of trend stationarity finds all the variables to reject the stationarity hypothesis. However, post differencing the data sets, each of the six variables (D.ALSI, D.INDI, D.RESI, D.FINI, D.BANKDEV and D.IIP) confirm stationarity through the KPSS test. For each variable, the log-linear transformation methodology failed to successfully alter the data to take on stationarity nature.

When this test is based on the null of level stationarity for the monthly nominal data, it produces precisely the same outcomes as the hypothesis that tests trend stationarity.

Lo-MacKinlay test (unit root)

The Lo-MacKinlay test on the monthly nominal data rejects that ALSI and IIP have unit roots, while INDI, RESI, FINI and BANKDEV can make no such rejection. Given all the other data transformation requirements from the other two tests, it was established that each variable must be Lo-MacKinlay tested post differencing the data. This resulted in all the transformed variables (D.ALSI, D.INDI, D.RESI, D.FINI, D.BANKDEV and D.IIP) rejecting the unit root hypothesis at all the tested month periods (q).

4.1.4. Real Monthly Data

Table 4 summarises the findings of all the real monthly data stationarity testing.

Table 4: Summary of Stationarity Testing (Real Monthly)

Variable	**SIC lags suggested**	**ADF intercept only**	*P Value*	**ADF intercept & trend**	*P Value*	**KPSS trend stationary**	**KPSS level stationary**	**Lo-MacKinlay**	*Respective intervals(q)*
ALSIR	1	✔	0.006***	✔	0.0211**	✗	✗	✔	2;4;8;16
lnALSIR	1	✔	0.0068***	✔	0.0274**	✗	✗	✔	2;4;8;16
D.ALSIR	**1**	✔	**<0.0001*** **	✔	**<0.0001*** **	✔	✔	✔	**2;4;8;16**
INDIR	12	✗	0.1345	✗	0.3128	✗	✗	✗	-
lnINDIR	12	✗	0.1649	✗	0.3465	✗	✗	✗	-
D.INDIR	**11**	✔	**<0.0001*** **	✔	**<0.0001*** **	✔	✔	✔	**2;4;8;16**
RESIR	12	✗	0.1406	✗	0.1577	✗	✔	✗	-
lnRESIR	12	✗	0.1453	✗	0.1845	✗	✗	✗	-
D.RESIR	**11**	✔	**<0.0001*** **	✔	**<0.0001*** **	✔	✔	✔	**2;4;8;16**
FINIR	1	✔	0.0137**	✔	0.068*	✗	✗	✗	-
lnFINIR	1	✔	0.0087***	✔	0.0502*	✗	✗	✗	-
D.FINIR	**11**	✔	**<0.0001*** **	✔	**<0.0001*** **	✔	✔	✔	**2;4;8;16**
RBankDev	12	✗	0.5197	✗	0.6868	✗	✗	✔	4;8;16
lnRBankDev	12	✗	0.5269	✗	0.6983	✗	✗	✔	4;8;16
D.RBankDev	**11**	✔	**<0.0001*** **	✔	**<0.0001*** **	✔	✔	✔	**2;4;8;16**

✔ Stationarity nature concluded for corresponding data set
✗ Non-stationarity nature concluded for corresponding data set
*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

Augmented Dickey-Fuller test (unit root)

The ADF tests on the real monthly data with a constant but no trend in the equation, show that ALSIR and FINIR reject the unit root hypothesis, while INDIR, RESIR and RBANKDEV all show non-stationarity. Upon applying differencing, however, all the variables (D.INDIR, D.RESIR and D.RBANKDEV) reject the unit root hypothesis.

The inclusion of a trend in the ADF test delivers similar results. ALSIR and FINIR are still the only variables to reject the unit root (however this time at the 95% and 90% confidence level respectively), while the remaining monthly real data sets (INDIR, RESIR and RBANKDEV) all fail to reject the unit root test without differencing. Applying differencing allows the sets of D.INDIR, D.RESIR and D.RBANKDEV to reject the unit root.

Kwiatkowski-Phillips-Schmidt-Shin test

Similarly to the nominal monthly testing results, the KPSS test on the null hypothesis of trend stationarity for the real monthly data finds all the variables to reject the stationarity hypothesis. However, post differencing the data sets, each of the five variables (D.ALSIR, D.INDIR, D.RESIR, D.FINIR and D.RBANKDEV) confirm stationarity through the KPSS test. For each variable, the log-linear transformation methodology failed to successfully alter the data to show stationarity nature.

When this test is based on the null of level stationarity for the monthly real data, it produces precisely the same outcomes as the hypothesis that tests trend stationarity.

Lo-MacKinlay test (unit root)

The Lo-MacKinlay test on the monthly real data initially rejects that ALSIR and RBANKDEV have unit roots, while INDIR, RESIR and FINIR data can make no such rejection. However, given the data transformation requirements from the other two tests, it was established that each variable must to be Lo-MacKinlay tested post differencing the data. This resulted in all the transformed variables (D.ALSIR, D.INDIR, D.RESIR, D.FINIR and D.RBANKDEV) rejecting the unit root hypothesis for all the monthly intervals (q).

4.2. Granger-causality Tests

Granger-causality tests are conducted on the following bivariate regressions, using 1 to 6 lags, l, for both nominal and real data (Sayed et al., 2017). The tests use the variable data time series' which passed all three of the stationarity tests above.

The null hypothesis for each of the pairs tested is that no Granger-causality exists, while the alternative is that Granger-causality is observed. F-tests (vector auto regression tests) are conducted with the joint hypothesis that the co-efficients, β1 through β6, are zero for quarterly nominal and real data when GDP and IIP are used as the economic variables and then again for monthly nominal and real data when IIP is used to proxy for economic activity (Sayed et al., 2017).

4.2.1. Results for Quarterly Data

Table 5 and Table 6 show the results for the pairwise Granger-causality tests for the nominal quarterly data, using GDP and IIP respectively for the economic indicator. The null hypotheses for these results are illustrated in the equations below:

Using GDP as the economic variable:

$$D.GDP_t = \alpha_0 + \alpha_1 D.GDP_{t-1} + \dots + \alpha_l D.GDP_{t-l} + \beta_1 ALSI_{t-1} + \dots + \beta_l ALSI_{t-l} + \mu_t \quad (1)^4$$

$$ALSI_t = \alpha_0 + \alpha_1 ALSI_{t-1} + \dots + \alpha_l ALSI_{t-l} + \beta_1 D.GDP_{t-1} + \dots + \beta_l D.GDP_{t-l} + \varepsilon_t \quad (2)$$

$$D.GDP_t = \alpha_0 + \alpha_1 D.GDP_{t-1} + \dots + \alpha_l D.GDP_{t-l} + \beta_1 D.INDI_{t-1} + \dots + \beta_l D.INDI_{t-l} + \mu_t \quad (3)$$

$$D.INDI_t = \alpha_0 + \alpha_1 D.INDI_{t-1} + \dots + \alpha_l D.INDI_{t-l} + \beta_1 D.GDP_{t-1} + \dots + \beta_l D.GDP_{t-l} + \varepsilon_t \quad (4)$$

$$D.GDP_t = \alpha_0 + \alpha_1 D.GDP_{t-1} + \dots + \alpha_l D.GDP_{t-l} + \beta_1 lnRESI_{t-1} + \dots + \beta_l lnRESI_{t-l} + \mu_t \quad (5)$$

$$D.RESI_t = \alpha_0 + \alpha_1 D.RESI_{t-1} + \dots + \alpha_l D.RESI_{t-l} + \beta_1 D.GDP_{t-1} + \dots + \beta_l D.GDP_{t-l} + \varepsilon_t \quad (6)$$

$$D.GDP_t = \alpha_0 + \alpha_1 D.GDP_{t-1} + \dots + \alpha_l D.GDP_{t-l} + \beta_1 D.FINI_{t-1} + \dots + \beta_l D.FINI_{t-l} + \mu_t \quad (7)$$

$$D.FINI_t = \alpha_0 + \alpha_1 D.FINI_{t-1} + \dots + \alpha_l FINI_{t-l} + \beta_1 D.GDP_{t-1} + \dots + \beta_l D.GDP_{t-l} + \varepsilon_t \quad (8)$$

$$D.GDP_t = \alpha_0 + \alpha_1 D.GDP_{t-1} + \dots + \alpha_l D.GDP_{t-l} + \beta_1 D.BANKDEV_{t-1} + \dots + \beta_l D.BANKDEV_{t-l} + \mu_t \quad (9)$$

$$D.BANKDEV_t = \alpha_0 + \alpha_1 D.BANKDEV_{t-1} + \dots + \alpha_l D.BANKDEV_{t-l} + \beta_1 D.GDP_{t-1} + \dots + \beta_l D.GDP_{t-l} + \varepsilon_t \quad (10)$$

4

In the terms "GDP_t", "$ALSI_t$", "$INDI_t$" etc. the *t* represents the point in time (t) that the variables are measured at.
α_1 and β_1 represent the co-efficients of a linear regression model, where μ_t and ε_t represent the respective residuals of the linear regression model (Wooldridge, 2009).

Using IIP as the economic variable:

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 ALSI_{t-1} + \dots + \beta_l ALSI_{t-l} + \mu_t \quad (11)$$

$$ALSI_t = \alpha_0 + \alpha_1 ALSI_{t-1} + \dots + \alpha_l ALSI_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (12)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.INDI_{t-1} + \dots + \beta_l D.INDI_{t-l} + \mu_t \quad (13)$$

$$D.INDI_t = \alpha_0 + \alpha_1 D.INDI_{t-1} + \dots + \alpha_l D.INDI_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (14)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RESI_{t-1} + \dots + \beta_l D.RESI_{t-l} + \mu_t \quad (15)$$

$$D.RESI_t = \alpha_0 + \alpha_1 D.RESI_{t-1} + \dots + \alpha_l D.RESI_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (16)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.FINI_{t-1} + \dots + \beta_l D.FINI_{t-l} + \mu_t \quad (17)$$

$$D.FINI_t = \alpha_0 + \alpha_1 D.FINI_{t-1} + \dots + \alpha_l D.FINI_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (18)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.BANKDEV_{t-1} + \dots + \beta_l D.BANKDEV_{t-l} + \mu_t \quad (19)$$

$$D.BANKDEV_t = \alpha_0 + \alpha_1 D.BANKDEV_{t-1} + \dots + \alpha_l D.BANKDEV_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (20)$$

Table 5: Nominal Quarterly Granger Test (GDP)

Table 5. Pairwise Granger-causality tests on nominal quarterly: D.GDP, ALSI, D.INDI, D.RESI, D.FINI and D.BANKDEV.

	1	2	3	4	5	6	7	8	9	10
No. of Lags	**From ALSI to D.GDP**	**From D.GDP to ALSI**	**From D.INDI to D.GDP**	**From D.GDP to D.INDI**	**From D.RESI to D.GDP**	**From D.GDP to D.RESI**	**From D.FINI to D.GDP**	**From D.GDP to D.FINI**	**From D.BANKDEV to D.GDP**	**From D.GDP to D.BANKDEV**
1	**0.0001*** **	0.869	**0.023** **	0.941	**0.0001*** **	0.324	0.336	0.771	**0.022** **	0.751
2	**0.055***	**0.059***	0.165	**0.0001*** **	0.495	0.455	0.399	**0.076***	0.132	0.578
3	**0.063***	0.204	0.127	**0.05***	**0.001*** **	**0.045** **	0.702	0.866	0.357	0.973
4	0.203	0.728	0.747	**0.078***	0.175	0.461	**0.014** **	**0.013** **	0.129	0.559
5	0.15	0.231	0.779	0.678	**0.0001*** **	0.758	0.156	0.771	0.147	0.521
6	**0.01** **	0.353	0.256	0.123	**0.05***	0.521	0.329	0.831	0.345	0.699

Notes: The Granger-causality tests are conducted using nominal quarterly data for six lags
Reported are the probability values of the null hypothesis of no Granger-causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

Table 6: Nominal Quarterly Granger Test (IIP)

Table 6: Pairwise Granger-causality tests on nominal quarterly: D.IIP, ALSI, D.INDI, lnRESI, D.FINI and D.BANKDEV.

	11	12	13	14	15	16	17	18	19	20
No. of Lags	**From ALSI to D.IIP**	**From D.IIP to ALSI**	**From D.INDI to D.IIP**	**From D.IIP to D.INDI**	**From D.RESI to D.IIP**	**From D.IIP to D.RESI**	**From D.FINI to D.IIP**	**From D.IIP to D.FINI**	**From D.BANKDEV to D.IIP**	**From D.IIP to D.BANKDEV**
1	**0.004*** **	**0.075***	**0.009*** **	0.652	**0.017** **	0.247	0.675	0.863	0.675	0.935
2	**0.03** **	**0.052***	0.102	0.299	**0.098***	0.992	0.352	0.275	0.212	**0.003*** **
3	0.732	0.139	0.174	0.384	0.458	0.22	**0.005*** **	**0.007*** **	0.422	0.398
4	0.227	0.765	0.429	0.93	0.307	0.976	**0.01** **	0.145	0.109	0.883
5	0.426	0.576	**0.085***	0.963	0.585	0.554	**0.015** **	0.565	0.568	0.227
6	**0.022** **	0.118	0.119	0.78	0.13	0.586	0.301	0.446	0.149	**0.022** **

Notes: The Granger-causality tests are conducted using nominal quarterly data for six lags
Reported are the probability values of the null hypothesis of no Granger-causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

The results in Table 5 show that for nominal quarterly data unidirectional causality exists between the ALSI and D.GDP for lag 1 (99% confidence level), lag 3 (90%) and lag 6 (95%). For lag 2 bidirectional causality is observed at the 90% confidence level. At lag 4 and 5 there is independence present between ALSI and D.GDP. When D.INDI is used as the market proxy, there is independence (no causality) present at lag 5 and 6, unidirectional causality exists at lag 1 (95%) and reverse causality is present at lags 2 (99%), 3 (90%) and 4 (90%). When D.RESI is used as the market proxy, unidirectional causality exists at lag 1 (99%), 5 (99%) and 6 (90%), bidirectional causality at lag 3 and independence is observed for lags 2 and 4. When D.FINI is used as the market proxy, independence is observed for lags 1, 3, 5 and 6, while showing bidirectional causality at the 95% confidence level at lag 4 and reverse causality at lag 2 (90%). When the banking sector development is tested using D.BANKDEV as the proxy, lags 2 to 6 show independence between D.GDP and D.BANKDEV, and lag 1 indicating unidirectional causality at the 95% confidence level.

Therefore, for nominal quarterly data, strong evidence is presented supporting share prices as a leading indicator for changes in GDP when RESI and ALSI are used. This is not the case for INDI and FINI as these indicate reverse causality when they are used as the market proxy. Additionally, for nominal quarterly data, there is little to no evidence of any causal relationship between the banking sector's development and GDP.

Table 6 indicates that, for nominal quarterly data, bidirectional causality exists between the ALSI and D.IIP for lag 1 and 2, while lag 6 shows unidirectional causality at the 95% confidence level. Lag 3 to 5 show independence between the two variables. With D.INDI being used as the market proxy there is independence present from lag 2 to 4 and again at lag 6, but unidirectional at lag 1 (99%) and lag 5 (90%). When D.RESI is used as the market proxy, unidirectional causality exists at lag 1 (95%) and 2 (90%) and independence is observed for lags 3 to 6. When D.FINI is used as the market proxy, independence is observed for lags 1, 2 and 6, unidirectional causality at lag 4 and 5 at the 95% confidence level and bidirectional causality at the 99% confidence level at lag 3. Finally, when the banking sector development is tested as a leading indicator using D.BANKDEV as the proxy, lags 1, 3, 4 and 5 all show independence between IIP and D.BANKDEV, and lag 2 and 6 indicating reverse causality at the 99% and 95% confidence level respectively.

Therefore, for nominal quarterly data, some evidence is presented supporting share prices as a leading indicator for changes in IIP. Each market index performs a leading indicator role for IIP for two lags without any evidence of reverse causality. In this case, though, ASLI and FINI also show some bidirectional causality. For nominal quarterly data, there is again no evidence of the banking sector development leading IIP changes, but rather evidence of reverse causality.

Table 7 and Table 8 show the results for the pairwise Granger-causality tests for the real quarterly data. In this case, Table C uses the proven real quarterly stationary economic variable of the second differenced RGDP (D2.RGDP), while Table D shows the results for quarterly IIP, being a volume (not price dependent) index, and thus comparable with real and nominal data. IIP can be tested with the real variables to assess if there is a stronger causality versus what it had with quarterly nominal data.

The null hypotheses are illustrated in the equations below:

Using GDP as the economic variable:

$$D2.RGDP_t = \alpha_0 + \alpha_1 D2.RGDP_{t-1} + \dots + \alpha_l D2.RGDP_{t-l} + \beta_1 ALSIR_{t-1} + \dots + \beta_l ALSIR_{t-l} + \mu_t \quad (21)$$

$$ALSIR_t = \alpha_0 + \alpha_1 ALSIR_{t-1} + \dots + \alpha_l ALSIR_{t-l} + \beta_1 D2.RGDP_{t-1} + \dots + \beta_l D2.RGDP_{t-l} + \varepsilon_t \quad (22)$$

$$D2.RGDP_t = \alpha_0 + \alpha_1 D2.RGDP_{t-1} + \dots + \alpha_l D2.RGDP_{t-l} + \beta_1 D.INDIR_{t-1} + \dots + \beta_l D.INDIR_{t-l} + \mu_t \quad (23)$$

$$D.INDIR_t = \alpha_0 + \alpha_1 D.INDIR_{t-1} + \dots + \alpha_l D.INDIR_{t-l} + \beta_1 D2.RGDP_{t-1} + \dots + \beta_l D2.RGDP_{t-l} + \varepsilon_t \quad (24)$$

$$D2.RGDP_t = \alpha_0 + \alpha_1 D2.RGDP_{t-1} + \dots + \alpha_l D2.RGDP_{t-l} + \beta_1 D.RESIR_{t-1} + \dots + \beta_l D.RESIR_{t-l} + \mu_t \quad (25)$$

$$D.RESIR_t = \alpha_0 + \alpha_1 D.RESIR_{t-1} + \dots + \alpha_l D.RESIR_{t-l} + \beta_1 D2.RGDP_{t-1} + \dots + \beta_l D2.RGDP_{t-l} + \varepsilon_t \quad (26)$$

$$D2.RGDP_t = \alpha_0 + \alpha_1 D2.RGDP_{t-1} + \dots + \alpha_l D2.RGDP_{t-l} + \beta_1 D.FINIR_{t-1} + \dots + \beta_l D.FINIR_{t-l} + \mu_t \quad (27)$$

$$D.FINIR_t = \alpha_0 + \alpha_1 D.FINIR_{t-1} + \dots + \alpha_l D.FINIR_{t-l} + \beta_1 D2.RGDP_{t-1} + \dots + \beta_l D2.RGDP_{t-l} + \varepsilon_t \quad (28)$$

$$D2.RGDP_t = \alpha_0 + \alpha_1 D2.RGDP_{t-1} + \dots + \alpha_l D2.RGDP_{t-l} + \beta_1 D.RBANKDEV_{t-1} + \dots + \beta_l D.RBANKDEV_{t-l} + \mu_t \quad (29)$$

$$D.RBANKDEV_t = \alpha_0 + \alpha_1 D.RBANKDEV_{t-1} + \dots + \alpha_l D.RBANKDEV_{t-l} + \beta_1 D2.RGDP_{t-1} + \dots + \beta_l D2.RGDP_{t-l} + \varepsilon_t \quad (30)$$

Using IIP as the economic variable:

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 ALSIR_{t-1} + \dots + \beta_l ALSIR_{t-l} + \mu_t \quad (31)$$

$$ALSIR_t = \alpha_0 + \alpha_1 ALSIR_{t-1} + \dots + \alpha_l ALSIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (32)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.INDIR_{t-1} + \dots + \beta_l D.INDIR_{t-l} + \mu_t \quad (33)$$

$$D.INDIR_t = \alpha_0 + \alpha_1 D.INDIR_{t-1} + \dots + \alpha_l D.INDIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (34)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RESIR_{t-1} + \dots + \beta_l D.RESIR_{t-l} + \mu_t \quad (35)$$

$$D.RESIR_t = \alpha_0 + \alpha_1 D.RESIR_{t-1} + \dots + \alpha_l D.RESIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (36)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.FINIR_{t-1} + \dots + \beta_l D.FINIR_{t-l} + \mu_t \quad (37)$$

$$D.FINIR_t = \alpha_0 + \alpha_1 D.FINIR_{t-1} + \dots + \alpha_l D.FINIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (38)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RBANKDEV_{t-1} + \dots + \beta_l D.RBANKDEV_{t-l} + \mu_t \quad (39)$$

$$D.RBANKDEV_t = \alpha_0 + \alpha_1 D.RBANKDEV_{t-1} + \dots + \alpha_l D.RBANKDEV_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (40)$$

Table 7: Real Quarterly Granger Test (GDP)

Table 7. Pairwise Granger-causality tests on real quarterly: D2.RGDP, ALSIR, D.INDIR, D.RESIR, D.FINIR and D.RBANKDEV.

	21	22	23	24	25	26	27	28	29	30
No. of Lags	**From ALSIR to D2.RGDP**	**From D2.RGDP to ALSIR**	**From D.INDIR to D2.RGDP**	**From D2.RGDP to D.INDIR**	**From D.RESIR to D2.RGDP**	**From D2.RGDP to D.RESIR**	**From D.FINIR to D2.RGDP**	**From D2.RGDP to D.FINIR**	**From D.RBANKDEV to D2.RGDP**	**From D2.RGDP to D.RBANKDEV**
1	**0.028****	0.265	0.177	0.646	**0.015****	0.972	0.6	0.95	0.507	0.524
2	0.441	0.409	**0.087***	0.761	0.875	0.166	0.397	0.952	0.715	0.722
3	0.855	0.103	**0.096***	0.628	0.131	0.619	**0.0001*****	**0.007*****	**0.04****	0.992
4	0.142	0.186	0.9	0.901	0.929	0.754	**0.071***	0.199	**0.064***	0.852
5	0.73	0.964	0.884	0.412	0.613	0.564	0.838	0.26	0.194	0.441
6	**0.058***	0.159	0.59	0.871	0.195	**0.006*****	0.104	0.823	0.874	0.981

Notes: The Granger-causality tests are conducted using nominal quarterly data for six lags
Reported are the probability values of the null hypothesis of no Granger-causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

Table 8: Real Quarterly Granger Test (IIP)

Table 8. Pairwise Granger-causality tests on real quarterly: D.IIP, ALSIR, D.INDIR, D.RESIR, D.FINIR and D.RBANKDEV.

	31	32	33	34	35	36	37	38	39	40
No. of Lags	**From ALSIR to D.IIP**	**From D.IIP to ALSIR**	**From D.INDIR to D.IIP**	**From D.IIP to D.INDIR**	**From D.RESIR to D.IIP**	**From D.IIP to D.RESIR**	**From D.FINIR to D.IIP**	**From D.IIP to D.FINIR**	**From D.RBANKDEV to D.IIP**	**From D.IIP to D.RBANKDEV**
1	**0.0001*****	**0.055***	**0.015****	0.523	**0.018****	0.235	0.82	0.729	1	0.982
2	**0.051***	**0.067***	**0.096***	0.306	**0.062***	0.982	0.351	0.318	**0.056***	**0.008*****
3	0.725	0.221	0.173	0.385	0.38	0.244	**0.005*****	**0.012****	0.71	0.584
4	0.322	0.526	0.36	0.902	0.211	0.947	**0.009*****	0.253	0.259	0.937
5	0.398	0.579	**0.076***	0.879	0.422	0.555	**0.014****	0.638	0.199	0.437
6	**0.013****	0.141	0.113	0.837	**0.088***	0.619	0.332	0.44	0.187	0.129

Notes: The Granger-causality tests are conducted using nominal quarterly data for six lags
Reported are the probability values of the null hypothesis of no Granger-causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

Table 7 indicates that, for real quarterly data, unidirectional causality exists between ALSIR and D2.RGDP for lag 1 (95%) and 6 (90%), while lag 2 to 5 show independence. With D.INDIR being used as the market proxy there is independence present for lags 1, 4, 5 and 6, but unidirectional at lag 2 and 3 at the 90% confidence level. When D.RESIR is used as the market proxy, unidirectional causality exists at lag 1 (95%), reverse causality occurs at lag 6 (99%) and independence is observed for lags 2 to 5. With D.FINIR as the market proxy, strong bidirectional causality in observed at lag 3, unidirectional causality at lag 4 at the 90% confidence level and independence is observed for lags 1, 2, 5 and 6. Finally, when the banking sector development is tested as a leading indicator with D.RBANKDEV as the proxy, unidirectional causality is observed at lag 3 (95%) and 4 (90%), with independence observed for the remainder of the lags.

Therefore, for real quarterly data, some evidence is presented supporting (real) share prices as a leading indicator for changes in real GDP, but this is not the case for the RESI, which indicates some reverse causality at one lag. Each other market index performs a leading indicator role for real GDP for two lags. However, FINIR shows some bidirectional causality for one of the lags. Additionally, for real quarterly data, there is more compelling evidence of the banking sector development leading real GDP changes with two lags indicating unidirectional causality.

Table 8 indicates that, for real quarterly data, unidirectional causality exists between ALSIR and D.IIP for lag 6 (95%), bidirectional causality at lags 1 and 2, and independence between the variables for lags 3 to 5. With D.INDIR being used as the market proxy there is unidirectional causality present for lags 1 (95%), 2 (90%) and 5 (90%) and independence for lags 3, 4 and 6. When D.RESIR is used as the market proxy there is unidirectional causality present for lags 1 (95%), 2 (90%) and 6 (90%) and independence for lags 3 to 5. With D.FINIR as the market proxy, bidirectional causality in observed at lag 3, unidirectional causality at lag 4 (99%) and 5 (95%) and independence is observed for lags 1, 2 and 6. Finally, when the banking sector development is tested as a leading indicator with D.RBANKDEV as the proxy, bidirectional causality is observed at lag 2, with independence observed for the remainder of the lags.

Thus, for real quarterly data, there is again evidence presented supporting (real) share prices as leading indicators for changes in IIP. Each market index performs a leading indicator role for IIP for three lags. However, in this case, ALSIR and FINIR show some cases of bidirectional causality. Additionally, for real quarterly data, there is little evidence of the banking sector development leading IIP changes.

4.2.2. Results for Monthly Data

Table 9 shows the results for the pairwise Granger-causality tests for the nominal monthly data, where IIP is the only available economic variable. The null hypotheses for these results are illustrated in the equations below:

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.ALSIR_{t-1} + \dots + \beta_l D.ALSIR_{t-l} + \mu_t \quad (41)$$

$$D.ALSIR_t = \alpha_0 + \alpha_1 D.ALSIR_{t-1} + \dots + \alpha_l D.ALSIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (42)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.INDIR_{t-1} + \dots + \beta_l D.INDIR_{t-l} + \mu_t \quad (43)$$

$$D.INDIR_t = \alpha_0 + \alpha_1 D.INDIR_{t-1} + \dots + \alpha_l D.INDIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (44)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RESIR_{t-1} + \dots + \beta_l D.RESIR_{t-l} + \mu_t \quad (45)$$

$$D.RESIR_t = \alpha_0 + \alpha_1 D.RESIR_{t-1} + \dots + \alpha_l D.RESIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (46)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.FINIR_{t-1} + \dots + \beta_l D.FINIR_{t-l} + \mu_t \quad (47)$$

$$D.FINIR_t = \alpha_0 + \alpha_1 D.FINIR_{t-1} + \dots + \alpha_l D.FINIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (48)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RBANKDEV_{t-1} + \dots + \beta_l D.RBANKDEV_{t-l} + \mu_t \quad (49)$$

$$D.RBANKDEV_t = \alpha_0 + \alpha_1 D.RBANKDEV_{t-1} + \dots + \alpha_l D.RBANKDEV_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (50)$$

Table 9: Nominal Monthly Granger Test (IIP)

Table 9. Pairwise Granger-causality tests on nominal monthly D.IIP, D.ALSI, D.INDI, D.RESI, D.FINI and D.BANKDEV.

	41	42	43	44	45	46	47	48	49	50
No. of Lags	**From D.ALSI to D.IIP**	**From D.IIP to D.ALSI**	**From D.INDI to D.IIP**	**From D.IIP to D.INDI**	**From D.RESI to D.IIP**	**From D.IIP to D.RESI**	**From D.FINI to D.IIP**	**From D.IIP to D.FINI**	**From D.BANKDEV to D.IIP**	**From D.IIP to D.BANKDEV**
1	0.641	0.528	0.462	0.311	0.432	0.992	0.25	0.111	0.515	0.337
2	**0.059***	0.335	**0.042****	0.213	0.121	0.587	0.143	**0.051***	0.208	0.271
3	**0.036****	0.966	0.457	0.946	**0.006*****	0.243	0.226	0.646	0.402	0.334
4	0.402	0.719	**0.015****	0.553	0.333	0.636	**0.095***	0.352	0.251	0.7
5	**0.011****	0.296	0.354	0.203	0.524	0.148	0.274	0.298	**0.001*****	0.34
6	0.116	**0.061***	**0.04****	0.287	0.126	0.266	**0.073***	0.206	0.867	**0.0001*****

Notes: The Granger-causality tests are conducted using nominal quarterly data for six lags
Reported are the probability values of the null hypothesis of no Granger-causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

The results in Table 9 show that for nominal monthly data unidirectional causality exists between the D.ALSI and D.IIP for lag 2 (90% confidence level), lag 3 (95%) and lag 5 (95%). For lag 6, reverse causality is observed at the 90% confidence level and at lag 1 and 4 there is independence present between D.ALSI and D.IIP. When D.INDI is used as the market proxy, unidirectional causality exists at lags 2, 4 and 6 at the 95% confidence level and there is independence (no causality) present at lags 1, 3, and 5. When D.RESI is used as the market proxy, unidirectional causality exists at lag 3 at the 99% confidence level and independence is observed for the other five lags. When D.FINI is used as the market proxy, unidirectional causality is observed at the 90% confidence level for lag 4 and 6, independence is found at lags 1, 3 and 5 and reverse causality is apparent at lag 2 (90%). Finally, when the banking sector development is tested using D.BANKDEV as the proxy, lags 1 to 4 show independence between D.IIP and D.BANKDEV, lag 5 indicates unidirectional causality at the 99% confidence level and lag 6 shows reverse causality at the 99% confidence level.

Therefore, for nominal monthly data, there is again some evidence presented supporting share prices as a leading indicator for changes in IIP. This evidence is most strong for the INDI index. The presence of reverse causality is briefly observed for one lag when the ASLI is used as the market proxy, while all other market proxies only exhibit unidirectional causality for their respective lags. It is noted that RESI only indicates unidirectional causality for one lag. Additionally, for nominal monthly data, there is little to no evidence of any causal relationship between the banking sector's development and IIP. BANKDEV shows unidirectional causality for one leg and reverse causality for another, while mainly showing independence.

Table 10 shows the results for the pairwise Granger-causality tests for the real monthly data, where IIP is the only available economic variable. The null hypotheses for these results are illustrated in the equations below:

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.ALSIR_{t-1} + \dots + \beta_l D.ALSIR_{t-l} + \quad (51)$$

$$D.ALSIR_t = \alpha_0 + \alpha_1 D.ALSIR_{t-1} + \dots + \alpha_l D.ALSIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (52)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.INDIR_{t-1} + \dots + \beta_l D.INDIR_{t-l} + \mu_t \quad (53)$$

$$D.INDIR_t = \alpha_0 + \alpha_1 D.INDIR_{t-1} + \dots + \alpha_l D.INDIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (54)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RESIR_{t-1} + \dots + \beta_l D.RESIR_{t-l} + \mu_t \quad (55)$$

$$D.RESIR_t = \alpha_0 + \alpha_1 D.RESIR_{t-1} + \dots + \alpha_l D.RESIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (56)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.FINIR_{t-1} + \dots + \beta_l D.FINIR_{t-l} + \mu_t \quad (57)$$

$$D.FINIR_t = \alpha_0 + \alpha_1 D.FINIR_{t-1} + \dots + \alpha_l D.FINIR_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (58)$$

$$D.IIP_t = \alpha_0 + \alpha_1 D.IIP_{t-1} + \dots + \alpha_l D.IIP_{t-l} + \beta_1 D.RBANKDEV_{t-1} + \dots + \beta_l D.RBANKDEV_{t-l} + \mu_t \quad (59)$$

$$D.RBANKDEV_t = \alpha_0 + \alpha_1 D.RBANKDEV_{t-1} + \dots + \alpha_l D.RBANKDEV_{t-l} + \beta_1 D.IIP_{t-1} + \dots + \beta_l D.IIP_{t-l} + \varepsilon_t \quad (60)$$

Table 10: Real Monthly Granger Test (IIP)

Table 10. Pairwise Granger-causality tests on real monthly D.IIP, D.ALSI, D.INDI, D.RESI, D.FINI and D.BANKDEV.

	51	52	53	54	55	56	57	58	59	60
No. of Lags	**From D.ALSIR to D.IIP**	**From D.IIP to D.ALSIR**	**From D.INDIR to D.IIP**	**From D.IIP to D.INDIR**	**From D.RESIR to D.IIP**	**From D.IIP to D.RESIR**	**From D.FINIR to D.IIP**	**From D.IIP to D.FINIR**	**From D.RBANKDEV to D.IIP**	**From D.IIP to D.RBANKDEV**
1	0.795	0.718	0.579	0.45	0.404	0.917	0.315	0.177	0.629	0.794
2	**0.085***	0.457	**0.058***	0.333	0.163	0.695	0.186	0.1	0.158	0.722
3	**0.078***	0.839	0.641	0.835	**0.01****	0.209	0.313	0.774	0.217	0.584
4	0.393	0.761	**0.014****	0.623	0.323	0.633	**0.095***	0.43	0.233	0.623
5	**0.018****	0.277	0.4	0.177	0.517	0.141	0.274	0.239	**0.001*****	0.372
6	0.121	**0.049****	**0.039****	0.26	0.121	0.252	**0.067***	0.175	0.457	**0.001*****

Notes: The Granger-causality tests are conducted using nominal quarterly data for six lags
Reported are the probability values of the null hypothesis of no Granger-causality being present.
*** denotes significance at the 1% level.
** denotes significance at the 5% level.
* denotes significance at the 10% level.

The results in Table 10 show very similar results to Table 9, indicating that the inflation adjustment made little impact on the relationship analysis. The findings show that for real monthly data unidirectional causality exists between the D.ALSIR and D.IIP for lag 2 (90% confidence level), lag 3

(90%) and lag 5 (95%). For lag 6, reverse causality is observed at the 95% confidence level and at lag 1 and 4 there is independence present between D.ALSIR and D.IIP. When D.INDIR is used as the market proxy, unidirectional causality exists at lags 2 (90%), 4 (95%) and 6 (95%) and there is independence (no causality) present at lags 1, 3, and 5. When D.RESIR is used as the market proxy, unidirectional causality exists at lag 3 at the 95% confidence level and independence is observed for the other five lags. When D.FINIR is used as the market proxy, unidirectional causality is observed at the 90% confidence level for lag 4 and 6, and independence is found for the remaining lags tested. Finally, when the banking sector development is tested using D.RBANKDEV as the proxy, lags 1 to 4 show independence between D.IIP and D.RBANKDEV, lag 5 indicates unidirectional causality at the 99% confidence level and lag 6 shows reverse causality at the 99% confidence level.

Therefore, for real monthly data, the same conclusions can be drawn that held for the nominal monthly data in Table 9. The only exception to the conclusions is with regards to FINIR showing no reverse causality with IIP, which therefore adds strength to its leading indicator ability.

4.3. Summary of Findings:

4.3.1. Share Price Relationship with Economic Activity

Sayed et al. (2017) conclude that there is strong empirical evidence revealing that causality does exist between share prices and economic activity in South Africa. It found that the evidence is strong as it shows all four stock indices leading both GDP and industrial production. This study does not find as compelling evidence (which is explained at the end of this chapter), although it supports the finding that there is some indication of a relationship where share prices lead economic activity.

This study empirically finds that the different market indices have varying casual relationships with GDP and IIP depending on the period intervals (monthly or quarterly) as well as the nominal or real nature of the time series data. When quarterly nominal data is used, there is only evidence of the RESI and ALSI Granger-causing GDP, which may be explained by the ASLI and RESI correlation indicated in chapter 2. However, it seems that for nominal quarterly data, the market indices have better unidirectional causal relationships with IIP, where there are no indications of reverse causality, while all still maintaining fair evidence of unidirectional causality. For real quarterly data, the causal relationship of share prices is not obviously evident across the indices in their leading of GDP, however, they again provide good evidence of unidirectional causality for IIP. With regards to nominal monthly data, the INDI provides the strongest evidence of leading IIP, while RESI show minor indications. ALSI shows a leading relationship with IIP, however it also indicates some reverse causality. FINI holds no significant leading relationship with IIP for nominal monthly data. Similarly for the quarterly real indices which was tested to lead IIP, the real monthly data shows that INDI provides a good indication of leading IIP. ALSI is similar although shows some minor reverse causality while RESI and FINI show some minor indications of leading IIP.

Overall, it appears that the market indices have a leading relationship with IIP when looking at the quarterly and monthly data, but this relationship is most pronounced using real quarterly data. The more significant relationship that IIP has with quarterly data may be as a result of only using six lags for the monthly data in the causality testing. It would be worth investigating if an increased number of lags changed the findings for the monthly data. It appears that the market indices more consistently display a causal relationship IIP than with GDP. The market indices provide inconsistent relationship findings when tested with GDP, where only ALSI and RESI are strong leaders of GDP changes using the nominal quarterly data, while ALSI, INDI and FINI show some less significant causal relationships with GDP when comparing real data.

Where the market does provide an indication of having a leading relationship with IIP, there is scope and opportunity for policy setters and decision makers to monitor those share markets as a means of assisting their forecasts of economic changes. This will possibly allow for more prudence and accuracy in short term policies and decisions.

4.3.2. Banking Sector Development Relationship with Economic Activity

The interpretation of the banking sector is far simpler as a result of only testing one variable (BANKDEV). Across the assessment of quarterly and monthly, nominal and real data, there was no compelling evidence of banking asset levels having a causal relationship with GDP or IIP. Generally the Granger test resulted in a mix of outcomes including reverse and unidirectional relationship findings, and any relationship was generally only established for a minority of the lags tested. Only when RBANKDEV was tested with real GDP using quarterly data, was there an indication of a unidirectional causal relationship and therefore a leading indicator relationship.

These are new findings for the South African context and will require further interrogation in the future, perhaps with a different measure(s) for the banking sector development.

4.3.3. Differing Share Price Findings Explained

This study finds supportive, yet less compelling, evidence of Granger-causality existing between share prices and economic activity in South Africa in comparison to the findings of Sayed et al. (2017). The findings are noticeably different because of the stationarity assumptions regarding the variables tested. In this paper, the inclusion of additional stationarity testing result in further transformation of the majority of the data sets in order to satisfy the stationarity requirement, and thus satisfying the requirement for Granger-causality testing. Therefore, the stationarity nature of the variables in this study differ to that of Sayed et al. (2017) due to enforcing stricter stationarity testing.

Sayed et al. (2017) only makes use of the ADF stationarity test to prove data stationarity, which is argued to be insufficient to conclude on stationarity (Box-Steffensmeier et al., 2014). It also assumes that, where GDP fails to indicate stationarity through ADF, it can be differenced to be made stationary. The differenced GDP data is not actually empirically tested to conclude on stationarity before conducting the Granger testing. This paper indicates that differencing GDP once is insufficient to make it stationary. As a result of less extensive stationarity testing, Sayed et al. (2017) tests for causality on the original data sets of ALSI, INDI, FINI, RESI and IIP, as well as the differenced GDP data, which all showed stationarity using the ADF test only. This paper postulates that the Granger-causality test could not be conducted on those data sets as they were found to be non-stationary and needed to be further differenced to empirically indicate stationarity nature.

Where Granger-causality testing takes place using non-stationary there is a risk of producing spurious results (Box-Steffensmeier et al., 2014). Thus, the compelling evidence of Sayed et al. (2017), which indicates share prices Granger-cause economic activity, is questionable given the lack of confidence in its data's stationarity. This paper adds stationarity tests to increase confidence to the findings of the Granger-causality testing, however the increased stationarity testing (and thus further transformed data) produces results which conclude on share price causality with far less assurance.

It should also be noted that, as much as this paper adds more emphasis to stationarity testing, it certainly does not exhaust the scope available. This means that there is more that can be tested and assessed in order to gain even more confidence regarding the stationarity of the data (such as co-integration testing and Arch and Garch model assessments), which could be performed in future research. However, what this paper does indicate is the potential inaccuracies of the compelling findings of Sayed et al. (2017), which may have developed from the inaccurate assessment of stationarity.

Chapter 5: Conclusion

This paper aimed to prove whether share prices and the banking sector development are leading indicators of economic activity in South Africa. The findings were conducted through the use of Granger-causality tests, which followed a three-stage stationarity testing method, unique to this study. The share price data made use of multiple indices on the JSE (being the ALSI, INDI, RESI and FINI) to account for market segmentation and the banking sector development proxy was that of South Africa's banking institution's asset level changes, which had not been tested before. This study also used the nominal and real data for these variables to form a robust analysis of any possible relationship. The period of the analysis is from March 1998 to October 2017.

The empirical analysis shows that causality does seem to exist between share prices and economic activity, which supports the 'wealth effect theory' (Comincioli, 1996) and the inherent 'forward looking nature' of shares (Stock and Watson, 2003) as expected. The findings do indicate, though, that the causal effect more consistently applies when the share prices lead IIP rather than GDP, where there was evidence of reverse causality as opposed to consistent unidirectional causality which the indices revealed with IIP. It also found that the quarterly data provided the most significant causal relationship between share prices and IIP. The nominal and real share prices were both equally predictive of IIP at the quarterly data level. These findings, regarding the causal relationship of share prices and economic activity in South Africa, are less definite than the previous findings of Sayed et al. (2017), which is due to this paper's additional emphasis on the condition of data stationarity. By completing additional stationarity testing on the time series data before performing Granger-causality testing, this paper establishes empirical Granger-causality results which are more compelling than the results of Sayed et al. (2017). Thus, this paper finds a more robust methodology of testing for causality between share prices and economic activity and therefore also establishes more robust results, which ultimately show less of a strong leading relationship between share prices and economic activity in South Africa than when compared to Sayed et al. (2017).

The empirical analysis also shows that there is no basis for conclusion of causality to exist between the banking sector development and economic activity, regardless of whether the data is assessed as a quarterly or monthly level and regardless of whether looking to cause GDP or IIP. In this case, it is clear that the supply-leading hypothesis does not apply.

This paper is not able to finally conclude on a few issues. These were discussed in Chapter 4.3.3, and provide further research opportunity in the future. With regards to stationarity, further modelling and testing can be performed in order to gain more full assurance of the stationarity nature of the data being tested in order to more accurately test for causality. This additional stationarity testing can include Arch and Garch model assessments as well as co-integration testing. For causality testing, it may be useful to perform the Granger test for an increased number of lags for the monthly data in order to assess the casual relationship over a longer period of months. Finally, this was the first attempt to assess a relationship with the South African banking sector's development and economic activity. Future research may look to assess the relationship using a different banking sector variable, other than the level of banking institutional assets in the country.

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Appendix

1. Detail of stationarity test results

1.1. KPSS Testing

1.1.1. Nominal Quarterly Data

Nominal Quarterly Data

ALSI	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.157	0.0913	0.0709	0.0618	0.0577	0.0558	0.0548	0.0547	0.0551	0.0559	0.0572	0.0593
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

ALSI	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.546	0.313	0.24	0.207	0.191	0.183	0.178	0.176	0.176	0.176	0.179	0.183
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

INDI	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.255	0.145	0.108	0.0906	0.0821	0.0773	0.0744	0.0726	0.0715	0.071	0.0714	0.0725
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

INDI	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.312	0.178	0.133	0.111	0.1	0.0942	0.0902	0.0878	0.0861	0.0852	0.0852	0.0861
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnINDI	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.243	0.138	0.103	0.0869	0.0794	0.0753	0.0727	0.0712	0.0701	0.0697	0.07	0.0712
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnINDI	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.377	0.214	0.16	0.134	0.122	0.115	0.11	0.107	0.105	0.103	0.103	0.104
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.INDI	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0279	0.0287	0.0293	0.027	0.0319	0.0374	0.0409	0.0484	0.0523	0.0543	0.0588	0.0602
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.INDI	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0434	0.0445	0.0454	0.0419	0.0493	0.0578	0.0631	0.0744	0.0803	0.083	0.0893	0.0911
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

RESI	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0931	0.0563	0.0451	0.0412	0.0408	0.042	0.044	0.0466	0.0494	0.0522	0.0552	0.0589
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

RESI	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	2.17	1.23	0.926	0.787	0.717	0.673	0.64	0.614	0.59	0.568	0.549	0.533
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnRESI	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0885	0.0519	0.0409	0.0368	0.0362	0.0371	0.0389	0.0414	0.0444	0.0478	0.0515	0.0559
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnRESI	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	1.95	1.09	0.817	0.694	0.634	0.598	0.573	0.554	0.539	0.526	0.514	0.505
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.RESI	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0278	0.0259	0.0264	0.0277	0.0348	0.0428	0.0505	0.061	0.0688	0.074	0.0757	0.0751
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.RESI	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.028	0.0261	0.0266	0.0279	0.0352	0.0433	0.0511	0.0618	0.0698	0.0751	0.0769	0.0762
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

FINI	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.245	0.14	0.103	0.0841	0.0743	0.0685	0.0654	0.642	0.0641	0.065	0.0665	0.0685
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

FINI	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.258	0.148	0.109	0.089	0.0785	0.0724	0.0691	0.0677	0.0675	0.0684	0.0699	0.0719
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnFINI	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.219	0.126	0.0929	0.0765	0.0679	0.063	0.0606	0.0598	0.0601	0.0613	0.0631	0.0654
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnFINI	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.259	0.149	0.11	0.0906	0.0804	0.0745	0.0715	0.0705	0.0707	0.072	0.0738	0.0762
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.FINI	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0444	0.0489	0.05	0.0429	0.0457	0.0466	0.048	0.0536	0.058	0.0644	0.0708	0.0736
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.FINI	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.101	0.11	0.112	0.0965	0.102	0.104	0.107	0.118	0.127	0.14	0.152	0.157
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

BankDev	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.419	0.22	0.154	0.123	0.105	0.0939	0.0866	0.0817	0.0786	0.0768	0.0761	0.0765
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

BankDev	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	1.9	0.987	0.686	0.541	0.457	0.403	0.366	0.34	0.32	0.306	0.296	0.289
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnBankDev	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.404	0.212	0.149	0.118	0.101	0.0906	0.0836	0.079	0.076	0.0744	0.0738	0.0742
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnBankDev	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	1.91	0.997	0.693	0.547	0.462	0.408	0.371	0.344	0.324	0.31	0.3	0.293
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.BankDev	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0718	0.0582	0.486	0.0449	0.0433	0.0476	0.0492	0.0504	0.0515	0.0523	0.054	0.056
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.BankDev	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0856	0.0692	0.0577	0.0533	0.0548	0.0562	0.0579	0.0593	0.0605	0.0614	0.0633	0.0655
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

IIP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.119	0.0779	0.0627	0.0564	0.0561	0.057	0.0586	0.0606	0.063	0.0659	0.0693	0.0728
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

IIP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.372	0.241	0.192	0.17	0.167	0.167	0.168	0.171	0.174	0.179	0.184	0.189
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnIIP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.126	0.0813	0.0651	0.0584	0.0578	0.0586	0.0599	0.0618	0.064	0.0669	0.0701	0.0736
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnIIP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.37	0.237	0.188	0.167	0.163	0.162	0.163	0.165	0.168	0.172	0.177	0.182
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.IIP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.016	0.0215	0.0241	0.0232	0.0334	0.0401	0.0467	0.0538	0.0577	0.0665	0.0754	0.0836
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.IIP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0173	0.0232	0.0259	0.025	0.0359	0.0431	0.0502	0.0578	0.0619	0.0713	0.0808	0.0895
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

GDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.233	0.137	0.107	0.0966	0.095	0.0969	0.1	0.103	0.105	0.107	0.109	0.111
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

GDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	2.92	1.61	1.18	0.977	0.867	0.793	0.735	0.685	0.642	0.604	0.572	0.545
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnGDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.236	0.138	0.108	0.0975	0.0957	0.0976	0.101	0.104	0.106	0.108	0.11	0.112
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnGDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	2.95	1.62	1.19	0.982	0.871	0.796	0.737	0.687	0.644	0.606	0.574	0.547
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.GDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0298	0.027	0.0265	0.0268	0.0343	0.0436	0.054	0.0643	0.0703	0.0754	0.076	0.0812
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.GDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0558	0.0504	0.0492	0.0631	0.0798	0.0979	0.116	0.126	0.134	0.134	0.134	0.142
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

1.1.2. Real Quarterly Data

Real Quarterly Data

ALSIR	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.153	0.0883	0.0682	0.0593	0.0553	0.0533	0.0524	0.0522	0.0525	0.0533	0.0546	0.0566
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

ALSIR	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.537	0.306	0.234	0.201	0.185	0.177	0.172	0.17	0.17	0.17	0.173	0.177
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

INDIR	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.239	0.135	0.1	0.0836	0.0756	0.0711	0.0684	0.0669	0.066	0.0658	0.0664	0.0678
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

INDIR	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.274	0.155	0.115	0.096	0.0867	0.0814	0.0781	0.0761	0.0749	0.0745	0.0749	0.0763
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnINDIR	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.243	0.138	0.103	0.0869	0.0794	0.0753	0.0727	0.0712	0.0701	0.0697	0.07	0.0712
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnINDIR	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.377	0.214	0.16	0.134	0.122	0.115	0.11	0.107	0.105	0.103	0.103	0.104
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.INDIR	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.031	0.0303	0.0301	0.028	0.0323	0.0374	0.0411	0.048	0.0517	0.0538	0.0577	0.0596
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.INDIR	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0469	0.0458	0.0455	0.0422	0.0486	0.0564	0.0618	0.072	0.0774	0.0803	0.0857	0.0881
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

RESIR	trend stationarity										
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0923	0.0557	0.0447	0.041	0.0409	0.0423	0.0445	0.0472	0.0499	0.0526	0.0554	0.059
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

RESIR	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	2.14	1.21	0.916	0.781	0.714	0.672	0.641	0.616	0.592	0.57	0.55	0.534
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnRESIR	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0879	0.0515	0.0405	0.0365	0.036	0.037	0.0388	0.0413	0.0443	0.0476	0.0512	0.0555
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnRESIR	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	1.9	1.06	0.797	0.678	0.621	0.588	0.565	0.548	0.533	0.52	0.509	0.501
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.RESIR	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0289	0.0262	0.0265	0.0279	0.0351	0.0433	0.0517	0.0629	0.071	0.0751	0.0756	0.0747
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.RESIR	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0292	0.0265	0.0268	0.0283	0.0356	0.0439	0.0526	0.0641	0.0724	0.0766	0.0771	0.0761
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

FINIR	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.237	0.134	0.0983	0.0804	0.0708	0.0652	0.0622	0.061	0.0609	0.0617	0.0633	0.653
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

FINIR	level stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.243	0.138	0.101	0.0823	0.0725	0.0668	0.0637	0.0624	0.0623	0.0631	0.646	0.0667
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnFINIR	trend stationarity											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.21	0.119	0.0874	0.0719	0.0638	0.0591	0.0569	0.0562	0.0565	0.577	0.0595	0.0619
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnFINIR	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.239	0.136	0.1	0.0824	0.073	0.0677	0.65	0.0641	0.0644	0.0656	0.0675	0.07
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.FINIR	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0481	0.0503	0.0498	0.0432	0.0452	0.0462	0.0478	0.053	0.0572	0.0633	0.0693	0.0725
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.FINIR	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.103	0.107	0.105	0.0916	0.0956	0.0973	0.1	0.111	0.119	0.13	0.142	0.142
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

RBankDev	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.405	0.216	0.154	0.124	0.108	0.0971	0.0897	0.0844	0.0804	0.0777	0.0759	0.0752
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

RBankDev	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	1.9	1	0.704	0.561	0.479	0.425	0.387	0.358	0.335	0.317	0.304	0.294
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnRBankDev	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.391	0.209	0.149	0.12	0.104	0.0941	0.087	0.0819	0.0781	0.0755	0.0739	0.0732
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnRBankDev	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	1.9	1	0.705	0.562	0.48	0.427	0.388	0.359	0.337	0.319	0.306	0.296
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.RBankDev	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0578	0.0487	0.0424	0.0417	0.0463	0.0518	0.0579	0.0617	0.0636	0.0628	0.018	0.061
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.RBankDev	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0724	0.0608	0.0529	0.0519	0.0576	0.0642	0.0714	0.0759	0.0781	0.0771	0.0758	0.0748
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

RGDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.438	0.235	0.17	0.14	0.125	0.115	0.11	0.107	0.105	0.104	0.103	0.103
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

RGDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	2.22	1.17	0.826	0.663	0.571	0.513	0.473	0.444	0.423	0.406	0.391	0.38
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

lnRGDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.428	0.23	0.167	0.138	0.122	0.113	0.108	0.105	0.103	0.103	0.102	0.102
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

lnRGDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	2.21	1.16	0.822	0.66	569	0.511	0.472	0.444	0.423	0.406	0.392	0.381
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D.RGDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0747	0.0508	0.0427	0.0404	0.0424	0.046	0.0511	0.0569	0.0644	0.0718	0.0777	0.0833
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D.RGDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.163	0.111	0.0929	0.0876	0.0913	0.0986	0.109	0.12	0.134	0.147	0.157	0.166
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

D2.RGDP	*trend stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0133	0.0174	0.02	0.0209	0.0285	0.0356	0.0446	0.0481	0.0632	0.0748	0.0747	0.0832
Crit values	1%	0.216										
	5%	0.146										
	10%	0.119										

D2.RGDP	*level stationarity*											
lag length	0	1	2	3	4	5	6	7	8	9	10	11
Test Stat	0.0191	0.0248	0.0285	0.0297	0.0404	0.0502	0.0626	0.0675	0.0881	0.104	0.104	0.116
Crit values	1%	0.739										
	5%	0.463										
	10%	0.347										

1.1.3. Nominal Monthly Data

Nominal Monthly Data

ALSI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.509	0.264	0.183	0.143	0.119	0.103	0.0926	0.0847	0.0788	0.0742	0.0707	0.068	0.0658	0.0641	0.0628
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

ALSI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.34	0.695	0.48	0.374	0.311	0.269	0.241	0.219	0.204	0.191	0.182	0.174	0.168	0.164	0.16
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnALSI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.428	0.221	0.153	0.119	0.099	0.086	0.077	0.0705	0.0656	0.0619	0.0591	0.057	0.0554	0.0541	0.0531
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnALSI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.974	0.503	0.347	0.269	0.224	0.194	0.174	0.159	0.147	0.139	0.132	0.127	0.123	0.12	0.118
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.ALSI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0417	0.034	0.0322	0.0306	0.0303	0.0302	0.0303	0.0307	0.0308	0.0309	0.0312	0.0317	0.0334	0.0358	0.0381
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.ALSI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0542	0.0441	0.0418	0.0397	0.0393	0.0391	0.0392	0.0397	0.0399	0.04	0.0404	0.041	0.0433	0.0464	0.0493
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

INDI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.805	0.419	0.289	0.223	0.185	0.159	0.141	0.127	0.117	0.109	0.102	0.0974	0.0934	0.0902	0.0875
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

INDI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.1	0.575	0.396	0.306	0.253	0.218	0.193	0.174	0.16	0.149	0.14	0.133	0.128	0.123	0.119
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnINDI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.754	0.392	0.27	0.208	0.172	0.148	0.131	0.119	0.11	0.102	0.0964	0.0919	0.0883	0.0854	0.0831
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnINDI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.3	0.677	0.465	0.36	0.297	0.256	0.227	0.205	0.189	0.176	0.166	0.158	0.151	0.146	0.142
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.INDI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0311	0.0313	0.0314	0.0301	0.0306	0.0315	0.0313	0.0315	0.031	0.0303	0.0298	0.0295	0.0311	0.0328	0.0343
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.INDI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0391	0.0393	0.0394	0.0378	0.0384	0.0394	0.0932	0.0394	0.0387	0.0378	0.0372	0.0369	0.0389	0.0409	0.0429
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

RESI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.281	0.15	0.105	0.0822	0.0691	0.0607	0.0549	0.0508	0.0478	0.0457	0.0441	0.0431	0.0424	0.042	0.0418
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

RESI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	6039	3.34	2.3	1.78	1.47	1.27	1.13	1.02	0.943	0.882	0.834	0.795	0.763	0.737	0.714
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnRESI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.262	0.138	0.0956	0.0746	0.0623	0.0544	0.049	0.0451	0.0423	0.0403	0.0389	0.0379	0.0373	0.0369	0.0368
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnRESI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	5.77	3	2.05	1.58	1.3	1.12	0.996	0.904	0.834	0.78	0.738	0.704	0.677	0.655	0.637
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.RESI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0283	0.031	0.0301	0.0287	0.0278	0.0281	0.0283	0.0284	0.0291	0.0299	0.0309	0.0314	0.0342	0.0368	0.0395
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.RESI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0283	0.031	0.0301	0.0287	0.0278	0.0281	0.0283	0.0284	0.0291	0.0299	0.0309	0.0314	0.0342	0.0368	0.0395
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

FINI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.738	0.387	0.267	0.207	0.171	0.146	0.129	0.116	0.106	0.0982	0.0919	0.0869	0.0828	0.0795	0.0767
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

FINI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.827	0.433	0.299	0.232	0.191	0.164	0.145	0.13	0.119	0.11	0.103	0.0975	0.0929	0.0892	0.0861
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnFINI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.649	0.34	0.235	0.182	0.15	0.129	0.114	0.103	0.0941	0.0872	0.0818	0.0775	0.074	0.0712	0.0688
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnFINI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.815	0.428	0.296	0.229	0.189	0.163	0.144	0.13	0.119	0.11	0.103	0.0976	0.0932	0.0896	0.0867
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.FINI	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0354	0.038	0.0397	0.0424	0.0443	0.0454	0.045	0.0455	0.0443	0.0416	0.0406	0.0396	0.0409	0.0417	0.0423
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.FINI	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0731	0.0782	0.0815	0.0869	0.0905	0.0924	0.0916	0.0923	0.0897	0.0844	0.0823	0.0802	0.0827	0.0842	0.0854
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

BankDev	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.3	0.663	0.447	0.34	0.275	0.233	0.202	0.18	0.162	0.148	0.137	0.128	0.121	0.114	0.109
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

BankDev	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	5.7	2.89	1.95	1.48	1.2	1.01	0.874	0.774	0.697	0.636	0.587	0.546	0.513	0.484	0.46
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnBankDev	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.26	0.639	0.431	0.328	0.266	0.224	0.195	0.713	0.156	0.143	0.133	0.124	0.117	0.111	0.105
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnBankDev	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	5.75	2.92	1.97	1.49	1.21	1.02	0.881	0.781	0.703	0.642	0.592	0.552	0.518	0.489	0.464
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.BankDev	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0648	0.0679	0.0665	0.0641	0.0599	0.0584	0.0567	0.0535	0.0511	0.0491	0.0473	0.0454	0.046	0.0464	0.0469
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.BankDev	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0716	0.0749	0.0733	0.0706	0.066	0.0643	0.0624	0.0589	0.0561	0.0539	0.0519	0.0498	0.0505	0.0509	0.0514
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

IIP	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.414	0.24	0.172	0.137	0.115	0.101	0.0905	0.0831	0.0777	0.0738	0.0708	0.0687	0.0673	0.0663	0.0657
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

IIP	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.24	0.715	0.509	0.404	0.34	0.296	0.265	0.243	0.226	0.214	0.204	0.197	0.192	0.189	0.186
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnIIP	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.437	0.251	0.178	0.142	0.119	0.104	0.0934	0.0857	0.0801	0.076	0.0729	0.0707	0.0692	0.0682	0.0674
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnIIP	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.437	0.251	0.178	0.142	0.119	0.104	0.0934	0.0857	0.0801	0.076	0.0729	0.0707	0.0692	0.0682	0.0674
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.IIP	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.23	0.701	0.498	0.394	0.331	0.288	0.258	0.236	0.22	0.208	0.198	0.192	0.187	0.183	0.18
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.IIP	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0111	0.0186	0.023	0.0244	0.0267	0.0278	0.0278	0.0282	0.0292	0.0299	0.0315	0.0298	0.0344	0.0373	0.0412
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

1.1.4. Real Monthly Data

Real Monthly Data

ALSIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.494	0.256	0.177	0.138	0.115	0.0994	0.0889	0.0812	0.754	0.071	0.0676	0.649	0.0628	0.0612	0.0598
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

ALSIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.32	0.684	0.472	0.366	0.304	0.263	0.234	0.214	0.198	0.186	0.176	0.169	0.163	0.159	0.155
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnALSIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	423	0.218	0.15	0.117	0.0969	0.084	0.0751	0.0686	0.0637	0.0601	0.0572	0.0551	0.0534	0.0522	0.0512
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnALSIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.93	0.479	0.329	0.255	0.212	0.183	0.163	0.149	0.138	0.13	0.124	0.119	0.115	0.112	0.11
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.ALSIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0467	0.0375	0.0352	0.0331	0.0324	0.0319	0.0316	0.0318	0.0319	0.0319	0.0322	0.0326	0.0343	0.0365	0.0386
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.ALSIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0604	0.0485	0.0455	0.0428	0.0418	0.0411	0.0408	0.041	0.0411	0.0411	0.0415	0.0421	0.0442	0.0471	0.0498
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

INDIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.752	0.39	0.268	0.207	0.171	0.147	0.13	0.117	0.107	0.1	0.0941	0.0894	0.0857	0.0826	0.0801
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

INDIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.957	0.497	0.341	0.263	0.217	0.187	0.165	0.149	0.137	0.127	0.12	0.114	0.109	0.105	0.102
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnINDIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.754	0.392	0.27	0.208	0.172	0.148	0.131	0.119	0.11	0.102	0.0964	0.0919	0.0883	0.0854	0.0831
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnINDIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.3	0.677	0.465	0.36	0.297	0.256	0.227	0.205	0.189	0.176	0.166	0.158	0.151	0.146	0.142
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.INDIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0354	0.0349	0.0347	0.0329	0.033	0.0335	0.0329	0.0329	0.0322	0.0314	0.0309	0.0305	0.032	0.0335	0.0349
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.INDIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0443	0.0436	0.0434	0.041	0.0412	0.0417	0.0411	0.0409	0.0401	0.0391	0.0384	0.038	0.0398	0.0417	0.0434
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

RESIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.277	0.147	0.103	0.0808	0.0679	0.0596	0.054	0.05	0.0471	0.045	0.0436	0.0426	0.042	0.0417	0.0415
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

RESIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	6.32	3.3	2.27	1.75	1.45	1.25	1.11	1.01	0.933	0.873	0.826	0.788	0.758	0.732	0.711
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnRESIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.26	0.137	0.0946	0.0738	0.0616	0.0538	0.0484	0.0446	0.0418	0.0398	0.0384	0.0375	0.0369	0.0365	0.0364
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnRESIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	5.63	2.92	2	1.54	1.27	10.9	0.97	0.88	0.813	0.76	0.72	0.687	0.662	0.641	0.623
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.RESIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0302	0.0325	0.0316	0.0299	0.0287	0.0288	0.0288	0.0288	0.0294	0.0303	0.0313	0.0318	0.0346	0.0372	0.0399
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.RESIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0301	0.0324	0.0315	0.0298	0.0286	0.0288	0.0288	0.0287	0.0294	0.0302	0.0312	0.0318	0.0346	0.0371	0.0398
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

FINIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.72	0.376	0.259	0.2	0.165	0.141	0.124	0.111	0.102	0.0941	0.088	0.0831	0.0792	0.0759	0.0732
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

FINIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.772	0.402	0.277	0.214	0.176	0.151	0.133	0.12	0.109	0.101	0.0945	0.0892	0.085	0.0815	0.0786
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnFINIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.623	0.325	0.224	0.173	0.143	0.122	0.108	0.097	0.0887	0.0822	0.077	0.0729	0.0696	0.0669	0.0647
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnFINIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.753	0.393	0.271	0.209	0.173	0.148	0.131	0.118	0.107	0.0996	0.0934	0.884	0.843	0.811	0.783
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.FINIR	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0402	0.0421	0.0437	0.046	0.0474	0.0478	0.0468	0.0468	0.0453	0.0427	0.0416	0.0405	0.0415	0.0422	0.0426
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.FINIR	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0789	0.0825	0.0855	0.0895	0.0921	0.0926	0.0906	0.0904	0.0875	0.0825	0.0803	0.0781	0.0801	0.0813	0.0821
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

RBankDev	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.26	0.64	0.434	0.331	0.269	0.228	0.2	0.178	0.162	0.149	0.139	0.13	0.123	0.117	0.112
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

RBankDev	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	5.71	2.9	1.96	1.49	1.21	1.02	0.891	0.792	0.716	0.656	0.608	0.568	0.535	0.507	0.483
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnRBankDev	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.21	0.619	0.419	0.32	0.26	0.221	0.193	0.173	0.157	0.144	0.134	0.126	0.119	0.114	0.109
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnRBankDev	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	5.71	2.9	1.96	1.49	1.21	1.02	0.89	0.792	0.716	0.657	0.608	0.569	0.536	0.508	0.484
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.RBankDev	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0608	0.0585	0.0555	0.0523	0.049	0.0472	0.0458	0.044	0.0429	0.0423	0.0417	0.0411	0.0426	0.0442	0.046
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.RBankDev	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0734	0.0705	0.0669	0.0629	0.0589	0.0568	0.055	0.0529	0.0515	0.0508	0.0499	0.0492	0.051	0.0529	0.055
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

IIP	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.414	0.24	0.172	0.137	0.115	0.101	0.0905	0.0831	0.0777	0.0738	0.0708	0.0687	0.0673	0.0663	0.0657
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

IIP	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.24	0.715	0.509	0.404	0.34	0.296	0.265	0.243	0.226	0.214	0.204	0.197	0.192	0.189	0.186
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

lnIIP	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.437	0.251	0.178	0.142	0.119	0.104	0.0934	0.0857	0.0801	0.076	0.0729	0.0707	0.0692	0.0682	0.0674
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

lnIIP	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.437	0.251	0.178	0.142	0.119	0.104	0.0934	0.0857	0.0801	0.076	0.0729	0.0707	0.0692	0.0682	0.0674
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

D.IIP	*trend stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	1.23	0.701	0.498	0.394	0.331	0.288	0.258	0.236	0.22	0.208	0.198	0.192	0.187	0.183	0.18
Crit values	1%	0.216													
	5%	0.146													
	10%	0.119													

D.IIP	*level stationarity*														
lag length	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Test Stat	0.0111	0.0186	0.023	0.0244	0.0267	0.0278	0.0278	0.0282	0.0292	0.0299	0.0315	0.0298	0.0344	0.0373	0.0412
Crit values	1%	0.739													
	5%	0.463													
	10%	0.347													

1.2. Lo-MacKinlay Testing

1.2.1 Nominal Quarterly Data

Nominal Quarterly Data

Variable	**q =**	**2**	**4**	**8**	**16**
ALSI	p > lzl	**0.0003*** **	**0.0016*** **	0.4497	0.5603
INDI	p > lzl	0.4566	0.1319	0.9992	0.5606
lnINDI	p > lzl	0.0663*	0.0315**	0.8625	0.4569
D.INDI	**p > lzl**	**0.0001*** **	**0.0243** **	**0.0343** **	0.2489
RESI	p > lzl	0.0239**	0.0178**	0.8856	0.9586
lnRESI	p > lzl	0.0054***	0.0151**	0.9796	0.7927
D.RESI	**p > lzl**	**0.003*** **	**0.0368** **	**0.0434** **	0.2413
FINI	p > lzl	0.8235	0.168	0.503	0.617
lnFINI	p > lzl	0.7589	0.0517*	0.3218	0.4807
D.FINI	**p > lzl**	**<0.0001*** **	**0.013** **	**0.0321** **	0.1913
BankDev	p > lzl	0.0084***	<0.0001***	0.0004***	0.0031***
lnBankDev	p > lzl	0.0102**	<0.0001***	0.0006***	0.004***
D.BankDev	**p > lzl**	**0.0004*** **	**0.0461** **	**0.0541* **	0.242
IIP	p > lzl	0.1568	0.5126	0.1406	0.3064
lnIIP	p > lzl	0.2005	0.572	0.1523	0.3182
D.IIP	**p > lzl**	**<0.0001**	**0.0115** **	**0.0255** **	0.1601
GDP	p > lzl	0.4929	0.2719	0.4699	0.7103
lnGDP	p > lzl	0.4866	0.2558	0.476	0.7146
D.GDP	**p > lzl**	**0.0001*** **	**0.0399** **	**0.0366** **	0.2691

*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

1.2.2 Real Quarterly Data

Real Quarterly Data

Variable	**q =**	**2**	**4**	**8**	**16**
ALSIR	p > lzl	**0.0002*** **	**0.0004*** **	0.2944	0.4254
INDIR	p > lzl	0.3024	0.0553*	0.7833	0.4644
lnINDI	p > lzl	0.0663**	0.0315**	0.8625	0.4569
D.INDIR	**p > lzl**	**0.0001*** **	**0.0291** **	**0.0348** **	0.2442
RESIR	p > lzl	0.0317**	0.013**	0.8411	0.9736
lnRESIR	p > lzl	0.0056***	0.0105**	0.9286	0.8475
D.RESIR	**p > lzl**	**0.0023*** **	**0.0396** **	**0.0429** **	0.2405
FINIR	p > lzl	0.9703	0.0754*	0.3062	0.4813
lnFINIR	p > lzl	0.4271	0.0109**	0.148	0.3373
D.FINIR	**p > lzl**	**<0.0001*** **	**0.0139** **	**0.0335** **	0.1908
RBankDev	p > lzl	0.0739*	0.0003***	0.0322**	0.0128**
lnRBankDev	p > lzl	0.0591*	0.0003***	0.0355**	0.0138**
D.RBankDev	**p > lzl**	**0.0004*** **	**0.0472** **	**0.0432** **	0.2284
RGDP	p > lzl	0.0001***	<0.0001***	0.0409**	0.1296
lnRGDP	p > lzl	0.0001***	<0.0001***	0.0441**	0.1402
D.RGDP	p > lzl	0.068**	0.2565	0.1001	0.2711
D2.RGDP	p > lzl	**<0.0001**	**0.006*** **	**0.0322** **	0.1535

*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

1.2.3 Nominal Monthly Data

Nominal Monthly Data

Variable	**q =**	**2**	**4**	**8**	**16**
ALSI	p > lzl	0.0018***	0.0008***	0.0077***	0.2243
lnALSI	p > lzl	0.0001***	<0.0001***	0.0005***	0.1165
D.ALSI	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0033*** **
INDI	p > lzl	0.3551	0.3275	0.6168	0.7858
lnINDI	p > lzl	0.2013	0.186	0.3007	0.6502
D.INDI	p > lzl	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0026*** **
RESI	p > lzl	0.0724*	0.9153	0.5425	0.6386
lnRESI	p > lzl	0.1869	0.4445	0.1618	0.9772
D.RESI	p > lzl	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0021*** **
FINI	p > lzl	0.9732	0.7904	0.6303	0.6811
lnFINI	p > lzl	0.607	0.4946	0.7109	0.5375
D.FINI	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0025*** **
BankDev	p > lzl	0.7786	0.4778	0.0693*	0.0166**
lnBankDev	p > lzl	0.7649	0.3918	0.0484**	0.0117**
D.BankDev	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001**	**0.0038*** **
IIP	p > lzl	<0.0001***	0.0001***	0.0055***	0.0243**
lnIIP	p > lzl	<0.0001***	0.0001***	0.0085***	0.0294**
D.IIP	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.002*** **

*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.

1.2.4 Real Monthly Data

Real Monthly Data

Variable	q =	2	4	8	16
ALSIR	p > lzl	0.0013***	0.0003***	0.0011***	0.0788*
lnALSIR	p > lzl	0.0001***	<0.0001***	<0.0001***	0.0311**
D.ALSIR	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0035*** **
INDIR	p > lzl	0.2795	0.2187	0.3472	0.4731
lnINDIR	p > lzl	0.2013	0.186	0.3007	0.6502
D.INDIR	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0027*** **
RESIR	p > lzl	0.0729*	0.9215	0.4078	0.7488
lnRESIR	p > lzl	0.2092	0.4128	0.1119	0.8622
D.RESIR	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0021*** **
FINIR	p > lzl	0.8122	0.9919	0.9434	0.3776
lnFINIR	p > lzl	0.7691	0.7239	0.8672	0.231
D.FINIR	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0026*** **
RBankDev	p > lzl	0.3434	0.0617*	0.0059***	0.0443**
lnRBankDev	p > lzl	0.354	0.0429**	0.0035***	0.0363**
D.RBankDev	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.0042*** **
IIP	p > lzl	<0.0001***	0.0001***	0.0055***	0.0243**
lnIIP	p > lzl	<0.0001***	0.0001***	0.0085***	0.0294**
D.IIP	**p > lzl**	**<0.0001*** **	**<0.0001*** **	**<0.0001*** **	**0.002*** **

*** Denotes significance at the 1% level.
** Denotes significance at the 5% level.
* Denotes significance at the 10% level.