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Testing the inverted-U hypothesis on economies with different levels of financial development.

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Abstract

The study seeks to understand the role that financial development has had on economic growth by testing the inverted-U hypothesis on three different countries of different levels of financial development, namely, Germany, Chile and Kenya.

South Africa is hailed as being one of the most financially developed economies. A stark contrast to a divided population, which is regarded as being one of the most unequal societies in the world. We test the inverted-U theory on countries with different levels of financial development to examine whether the theory of economic growth driven by financial development is applicable to South Africa.

Using multivariate linear regression (MLR) and Vector Auto Regression (VAR), the research examines association and causality, if any, for a market-based (SMC) and a bank-based (PCE) induced growth.

The study found that both SMC and PCE are highly correlated to the GDP, but that only SMC has a causal relationship to GDP, suggesting that financial markets are better conditioned to grow the economy than banks are, for all levels of economic development. This evidence suggests that economic growth is most likely innovation-driven and South Africa's innovation barometer is sub-par. The lesson for South Africa is that the country must put more emphasis on innovation-based growth if it is to reduce poverty and increase growth.

Keywords: Inverted-U hypothesis, inequality, innovation, VAR

Declaration

I declare that this research project is my own work. It is submitted in partial fulfilment of the requirements of the degree of Master of Business Administration at the Gordon Institute of Business Science, University of Pretoria. It has not been submitted before for any degree or examination at any other University. I further declare that I have obtained the necessary authorisation and consent to carry out this research.

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Glossary

AEG	-	Augmented Engle-Granger
AIC	-	Akaike Information Criterion
EMH	-	Efficient market hypothesis
FD	-	Financial development
GCI	-	Global competitiveness index
GDP	-	Gross domestic product
IMF	-	International monetary fund
M1	-	Notes in circulation
M2	-	M1+short-term deposits+24hr market funds
MLR	-	Multiple linear regression
PCE	-	Private credit extension
SMC	-	Stock market capitalization
SMT	-	Stock market turnover
VAR	-	Vector auto regression
VIF	-	Variance Inflation Factor

CHAPTER 1. Introduction to the research problem

1.1. Research title

Testing the inverted-U hypothesis on economies with different levels of financial development.

1.2. Introduction

The jury is still out as to whether efficient financial institutions and financial markets are associated with higher economic growth. On a balance of scales, the evidence (Arestis, Panicos, & Luintel, 2001; Beck, Chen, Lin, & Song, 2016; Berkes, Panizza, & Arcand, 2012; Law & Singh, 2014; Levine & Zervos, 2008) suggests there is economic growth that is spurred through financial development . The initial findings tend to be biased on a positive relationship, which is to say that financial development yields greater economic growth. Recent findings (Henderson, Papageorgiou, & Parmeter, 2013; Law & Singh, 2014; Samargandi, Fidrmuc, & Ghosh, 2015), however, point to an optimal level of finance which is sufficient and suitable for that particular economy that can drive the economic growth, after which further financial development starts to negatively impact economic growth. The assumption is that further financial enhancements that are beyond their intended purpose of improving transactions and trade, can only be of rent-seeking in nature (Bai, Philippon, & Savov, 2016). Since banks and financial markets are profit driven, they may tend to make the financial markets by sharing less information and thus increasing their market share profitability (Bai et al., 2016). This is crucial for policy-makers because they need to understand where economies lie on the curve and whether more financial development is necessary to foster economic growth.

The three countries under consideration are categorised by their level of financial development measured by combining the existing rankings from the Global Competitiveness Index (GCI) under the eighth pillar of financial market development and the International Monetary Fund (IMF) broad-based index of financial development (Schwab, 2018; Svirydzenka, 2016). These countries are therefore structurally different from a financial development perspective. Some may be developing through bank-based variables and some maybe driving their economies through market-based variables (Graff & Karmann, 2006). There are arguments for and against the capital structure.

Understanding the interplay between the financial structure and the participants in the economy is crucial in setting up policies and regulations in the financial services industry.

Developing countries are typically behind the technological curve and, as a result, focus more on capital accumulation; whilst more developed countries, are more focused on innovation (Rioja & Valev, 2014). It is therefore important for the financial structure to form an enabling environment or ecosystem to allow businesses to reach their potential.

1.3. The relevance of this research in a South African context

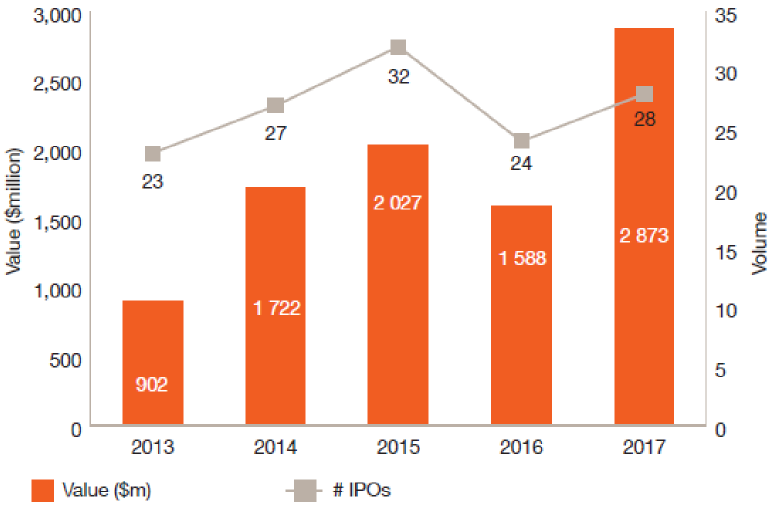
There are only three African countries that are ranked in the 2015 top 50 in terms of the global competitiveness index (GCI), financial market development (Schwab, 2018). Rwanda, South Africa, and Namibia are ranked 34th, 44th and 50th respectively. Whilst South Africa continues to develop its financial markets, widespread poverty is still a reality, as seen by growing inequality, and is often referred to as the most unequal country in the world (National development plan, 2011). With a Gini coefficient of 0.63 in 2015, Barros and Gupta (2017) conclude that, whilst income increases, poverty remains a predominant socio-economic issue. Their conclusions show that the income rise alone is not sufficient for poverty alleviation.

The South African economy is in a technical recession, after experiencing two consecutive quarters of negative growth, namely, -2.6% and -0.7% in the first and second quarter of 2018 respectively (Statistics South Africa, 2018a). The shrinking growth forms the backdrop for reduced agricultural yields, as the agricultural sector has not fully recovered from the 2016 drought, whilst manufacturing and trade weighed in on the negative growth output (Statistics South Africa, 2018a).

The inverted-U hypothesis argues that financial growth up to a certain level is positive for economic growth but ceases to contribute to contribute to growth thereafter, and may even tend to adversely affect economic growth (Berkes et al., 2012; Shen & Lee, 2006). In the early-stages of financial development, the inverted-U hypothesis holds that there is an acceleration of economic growth as financial institutions and markets enhance their capacities in managing transactions that are intended to improve trade and transactability in the economy.

South African financial institutions are known for their well-regulated and sound frameworks (de Kock, Petersen, & Mokoena, 2017) and are rank amongst the best in the world (Schwab, 2018).

Figure 1: IPO trends by year, 2013-2017



Source: (PWC, 2017)

Figure 1 illustrates Initial Price Offerings (IPOs), which represent new listings on the stock exchange in Africa. This shows a relatively active market, with 28 IPOs in 2017 valued at USD 2.9 billion. Eighty percent of the listings, measured by value, originated in the Johannesburg Stock Exchange (PWC, 2017).

Poverty alleviation in South Africa has not reflected the benefits from enhancements in financial development. At the end of the first quarter of 2018, for example, the unemployment level was 26.7%, with most of job losses year-on-year coming from manufacturing and trade (Statistics South Africa, 2018b).

It is in this context that this current study aims to contribute to the question of whether middle-income countries such as South Africa should be strengthening and promoting other growth-enhancing strategies in maintaining long-term economic growth—if, indeed, the inverted-U hypothesis holds.

1.4. Research purpose

The study aims to determine whether the financial development results in economic growth. This hypothesis is tested against countries at different levels of financial development as determined by eighth pillar of the GCI (Schwab, 2018) and the IMF Broad-Based Index for financial development (Svirydzenka, 2016). Once this is determined, the study aims to determine the financial development that is suitable to spur growth.

1.5. Research objectives

The fundamental question inherent in this research is: Does financial development lead to long-run economic growth, and whether this relationship is linear?

The study will focus only on three countries, which have been chosen using the IMF broad-based index for financial development and the GCI eighth pillar for financial market development. This provides some basis for inferences to be made on countries with various levels of economic development.

Figure 2: Research goals

Goal 1:	Determine whether financial development (market-based institutions) in low-income countries have any relationship with economic output, and whether this relationship is causal in nature.
Goal 2:	Determine whether financial development (market-based institutions) in middle-income countries have any relationship with economic output, and whether this relationship is causal in nature.
Goal 3:	Determine whether financial development (market-based institutions) in high-income countries have any relationship with economic output, and whether this relationship is causal in nature.
Goal 4:	Determine whether financial development (bank-based institutions) in low-income countries have any relationship with economic output, and whether this relationship is causal in nature.
Goal 5:	Determine whether financial development (bank-based institutions) in middle-income countries have any relationship with economic output, and whether this relationship is causal in nature

Goal 6:	Determine whether financial development (bank-based institutions) in high-income countries have any relationship with economic output, and whether this relationship is causal in nature.

Source: Own research

1.6. The scope of the research

The research scope focuses on understanding how much financial development can drive economic growth. Whilst it may point to financial development, it does not cover any specific structural heterogenetic effects on the different economies.

The limitations in the study pertain to the limited data in the World Bank database and to the fact the representative sample size is small. The delimitations in the study consist of the selection of macroeconomic elements that have been used by other researchers, which have in turn framed the theoretical basis of this research. The data is annual data for Germany, Chile, and Kenya and is available in the World Bank database (The World Bank, 2018).

CHAPTER 2. Literature review

2.1. Introduction

The nexus of financial development and how it relates to economic growth is widely researched literature (Beck, Levine, & Loayza, 2000; Chandio, 2014; Demir & Hall, 2017; Federici & Caprioli, 2009) and yet far from any conclusive evidence which would establish veracity as to what this relationship entails. The theoretical foundation of this relationship dates back to the neoclassical growth model (Solow, 1956), which mainly focused on capital formation between physical capital and labour productivity. Later neoclassical theorists (Cass, 1965; Phelps, 1961) argued that a unique optimum path for any initial capital-labour ratio and an initial price of investment goods can be chosen in such a way that the path will satisfy the optimal conditions which will asymptotically approach a stationary path, that is, the golden rule steady state. Underlying this neoclassical viewpoint is the exogenous element of technology, which endogenous growth theorists argued was not the case because the assumption of diminishing returns of capital or depreciation, in the production of growth output need not be correct. In fact, in an equilibrium, the unit output per capita can increase in a non-decreasing way but possibly at a rate that monotonically increases over time (Romer, 1986). This claim is supported by Alexiou and Vogiazas (2018), who highlight that growth is driven by present investments. Central in the analysis is the question of what type of investment matters for growth, and if indeed banks and financial markets are a fundamental driver of productivity. If, however, the financial sector develops only because of growth and the sophistication that comes with it, then what should inform policy to be able to deliver growth and prosperity?

Historically, this has been a debate centring on the banking system and its ability to actively spur innovation and entrepreneurship (Levine & Zervos, 2008). The advent and development of financial markets sparked a new debate on whether the markets were better suited to effectively allocate resources because of their more active participation in the economy (Levine & Zervos, 2008). This argument suggests that markets tend to be more efficient in allocating capital to entrepreneurs, but Philippon (2015) argues that over the last century, the cost of financial intermediation has risen, thus making financial markets less efficient because the trading activities do not necessarily provide value. Traders are incentivised to take on more risk because of the way in which they are compensated which can create market bubbles which are non-reflective of market fundamentals (Beck, Degryse, & Kneer, 2014). Trading activity can also be seen in a positive light, because it could be a result of conflicting opinions and as field experts aim to prove their viewpoint, the process could lead to an actual discovery or solution which could potentially result in technological advancement (Hasan, Horvath, & Mares, 2016).

An important function of the financial system in its role its primary role of reducing information asymmetry is to encourage efficient allocation of economic resources in a transparent and well-informed way through pricing mechanisms in an uncertain environment (Merton, 1992). Information asymmetry is most commonly used in decision economics (Colombage & Halabi, 2018) and describes a situation whereby one party has more material information than the other transacting party and can therefore use the scarce information to take advantage of the other in the transaction.

Financial development therefore posits the improvement of the financial system in by continuously improving in it quality and customer service delivery and also it its facilitation risk sharing and resource allocative efficiency (Beck et al., 2016). Moral hazard tends to compromise the value that information sharing can bring, and this can be seen in the distorted prices in less efficient markets; in severe levels of moral hazard, banks have a crucial responsibility for making sector decisions in order for the economy to grow (Peia & Roszbach, 2013). Moral hazard in this context can be defined as a credit counterparty taking more risk than what they are covered to take, thus increasing the overall exposure of the portfolio, because other non-risk taking counterparties will bear the risk (Torre, Feyen, & Ize, 2013). It is therefore ultimately the role of the bank that will assist both the supplier and consumer in overcoming the fear of asymmetric information and distrust that may tend to arise without the presence of the financial intermediary (Jaud, Kukenova, & Strieborny, 2012).

Another growth impediment that arises from asymmetric information is adverse selection, which is the idea that the aggregate prices may be slightly higher because banks and markets alike need to price in poor judgement in their role as assessors of eligibility for credit (Demir & Hall, 2017). This is counterproductive, because whilst financial intermediation is meant to lower prices, as they are well positioned to match borrowers and lenders, therefore reducing the searching costs for information (Kelly & Ljungqvist, 2012), they also price in for inefficiencies that arise in their method of aggregating.

Whilst there may exist information sharing, which reduces the searching costs for information and may induce an increase in total factor productivity through the savings rate, there is little evidence that supports increased savings as a result of financial development (Beck et al., 2000). As the banks become relatively large and influential in the economy, evidence suggests that instead of continuing to play their role of reducing information asymmetry, they stifle the environment by extracting informational rents from firms and protecting their establishment (Hsu, Tian, & Xu, 2014). This in turn reduces the firms' incentives to invest in long-term projects, which negatively affects capital accumulation.

A majority of literature, however, has favoured the presumption that, in the long-run, developing financial markets often results in increased economic activity and induces economic growth. From the perspective of total factor productivity, a more efficient banking system induces economic growth because more information is shared between the firms who need capital and the banks who provide capital (Levine, Loayza, & Beck, 2000). This observation is shared by Acs et al. (2006), who claim that technological or financial improvements often raise the level productivity of capital causing firms to re-invest at a higher rate. Capital formation, therefore, should not be thought of as independent but rather as a facilitator of growth. Similarly Beck et al. (2000) find that total factor productivity growth which directly results in GDP growth is induced by financial development which further creates an increased demand for financial intermediation and support.

Not only are the financial developments limited to banks, but they also spread across the industry, which includes insurance companies, stock and bond markets, and derivative markets (Čihák, Demirgüç-Kunt, Feyen, & Levine, 2012). These institutions will ensure that the best business idea is brought to life through the existing structures in the institutions that force rigorous screening and due diligence. If these institutions are allowed to operate independently, they tend to create a trusting environment which spurs further investments in the economy (Čihák et al., 2012). The more efficient and robust the financial intermediaries become, the greater is their relationship to economic growth (Hasan et al., 2016). A lack of trust in institutions and a weak regulatory framework are the major obstacles for innovation and economic growth (Aghion, Akcigit, & Howitt, 2015). He et al. (2017) funds a strong and positive correlation between the general level of trust that prevails in a specific country and its financial development, and in some instances the trust and reputation can even substitute for the regulatory framework, especially where the regulatory framework is weak or non-existent.

2.2. Financial development

The financial industry encompasses a variety of institutions (Čihák et al., 2012) which have a number of different instruments for specific markets which are guided and regulated by a legal framework that allows for credit to be extended (World Bank, 2016). Financial development is the ability to continuously extend credit, at the same time reducing the cost that comes with availing credit (World Bank, 2016). There are a number of methods to measure financial development: these are summarised in the Global Competitiveness Index's 8th pillar, which broadly measures the efficiency of the institutions in allocating capital as well as the trustworthiness and confidence that lenders and borrowers have in these institutions (Schwab, 2018). These two broad measures amplify the regulatory framework which (Levine et al., 2016) argue is key in reassuring investor confidence.

The other method, albeit similar to the GCI is the International Monetary Fund's broad-based index for financial development, which broadly identifies three aspects which describe the elements that constitutes financial development. namely these elements are, i) depth, which describes the level of penetration that there existing financial measures have in the economy, ii) access, which measures the potential opportunity that entrepreneur if they needed to transact and, iii) efficiency, which measure the affordability of both financial institutions and financial markets (Svirydzenka, 2016). Both of these methods seek to measure financial soundness and thus the role of financial intermediation in the economy. The International Monetary Fund (IMF broad-based index is different from the GCI index, because it separates the measures for financial institutions from those of financial markets (Svirydzenka, 2016), enabling policy-makers to view the two institutions separately to each other and verify their effectiveness in the economy. The separation of the index is shown below in Figure 1.

Figure 3: Financial development index pyramid

Source: Svirydzenka, 2016

2.3. Supply-leading hypothesis

Evidence from several researchers (Beck et al., 2016; Durusu-Ciftci, Ispir, & Yetkiner, 2017; Levine & Zervos, 2008; Peia & Roszbach, 2013) further suggests that over and above the correlative relationship between financial intermediation and output, there is in fact a direction or causality. Causality in this context means that financial enhancements of the industry may result in increased economic output. A supply-leading hypothesis is presented in the literature (Beck et al., 2016; Peia & Roszbach, 2013) and suggests that financial development leads to economic growth through providing an enabling environment where investors can reduce risk via securities markets and thus lower the cost of capital, in turn raising the investor appetite to make long-term investments. This is a deliberate policy stance that creates the environment for there to be various financial institutions such that financial services lead to economic growth.

Finance-led growth for relatively advanced economies is supported mostly when the financial enhancements stem from securities markets, because they tend to support new projects that banks would otherwise not fund (Peia & Roszbach, 2013). Countries and industries with higher growth opportunities show only a potential for growth and that this potential can be converted if commercial banks and financial markets assume more responsibility in technological engineering and innovation (Beck et al., 2014). This effect is, however, dependent on having securities market that is advanced enough to allow entrepreneurs to assume new projects without necessarily taking more risk. The notion effectively suggested is that both banks and financial markets are required to work optimally for an environment of economic growth to be developed (Arestis et al., 2001; Beck et al., 2016; Peia & Roszbach, 2013).

Similarly to arguments of risk reduction proposed by Peia & Roszbach (2013), Manganelli and Popov (2015) study the effect that financial advancement has on sectorial long-term volatility. Evidence suggests that there is a Pareto improvement in lowering the aggregate level of volatility in comparison to countries with a similar level of long-term economic growth, which is achieved by the securities markets reallocating resources to less volatile sectors which have a high correlation to the growing economy. The reduction in the aggregate long-term volatility paves the way for new investors to enter (Manganelli & Popov, 2015), suggesting that financial markets are facilitators for economic growth.

Whilst Durusu-Ciftci et al. (2017) support the supply-leading hypothesis, the conclusions differ from those of other researchers (such as Beck et al., 2016; Peia & Roszbach, 2013) by suggesting that the banks are more likely to support long-term productivity than the securities market.

2.4. Demand-leading hypothesis

There does, however, exist some counter-evidence to the supply-leading hypothesis. Demetriades and Hussein (1996) find that there no conclusive evidence that would suggest a finance led economy. Furthermore, there are heterogeneous impacts for different countries without any pattern or consistency to the level of their respective development. In some of countries, as the GDP grows, there tends to be an increase in the demand for finance related services—this reverse relationship supports the demand-following hypothesis, which suggests that the demand for finance is mainly as a result of increasing productivity and expansion of firms, who in-turn require financial support (Liu, 2003). These findings, however, do not consider the heterogeneous features that are specific to the various countries and do not specify the structure of financial development that is enhanced. Arcand et al. (2015) study the heterogenic financial composition for various countries and their interplay with the economy and conclude that each country tends to advance a financial system that support their respective economy. This effectively means that financial support follows productivity.

In countries with very dominant and deep financial markets, there tends to be a weak to non-existent impact on economic output relative to the growth in financial markets. In countries with a less developed and less dominant financial sector, this relationship is less mute because the impact of a finance related innovation is able to tap into a larger population of entrepreneurs. According to Arcand et al. (2015), there is an optimal level at which a further increases in financing starts to adversely effect productivity. Muteness in the securities market can be attributed to an increase in the speculative markets which tend not to be focused on improving productivity (Bai et al., 2016). This evidence suggests that there is a non-linear elasticity effect between progress and growth in the financial sector and productivity. There is initially a high elasticity with lower economic growth, which increases up to a certain level, where the economy has developed to such an extent that further financial sector improvements do not have a greater impact on the economy. This non-linearity is consistent with the results of Law and Singh (2014), who show that the financial market growth is beneficial but also experiences diminishing returns at a certain level.

Beck, Degryse and Kneer (2014) make a compelling argument supporting an intermediation role played by financial institutions, arguing that once the intermediation between customers placing funds (i.e., depositors) and borrowing customers (i.e., liabilities) has been fulfilled, further financial development does not yield any further long-run economic growth.

2.5. U-shaped hypothesis

Samargandi, Fidrmuc and Ghosh (2015) expand on the notion of optimal thresholds as pointed out in (Law & Singh, 2014) and submit that the relationship is not linear and therefore is not monotonic. They further demonstrate evidence of an inverted U-shaped relationship, supporting evidence presented by (Berkes et al., 2012) and (Beck et al., 2014). Shen and Lee (2006) also support the notion of an optimal threshold and demonstrate non-linearity amongst financial market growth and productivity, whereby an increase in a stock market index, does not result in GDP growth. The implications are meaningful, and whilst they may seem counter-intuitive because financial enhancements are meant to better the way businesses transact, they have pertinent policy implications. Policy-makers could focus more on improving financial intermediation and strengthening policies to ensure that they are relevant to the country's growth needs but the enhancements must remain relevant. Law and Singh (2014) argue that once a country reaches its optimal finance-led growth, it needs to then take measures to strengthen and promote other growth-enhancing strategies in maintaining long-run economic growth. When the real economy strengthens and becomes robust from financial deepening, more financial improvements tend to be less effective, and the demand-following hypothesis increases its dominance (Alexiou & Vogiazas, 2018).

Henderson, Papageorgiou and Parmeter (2013) test for causality whilst controlling for heterogeneity and nonlinearities. They find that over time the relationship is significantly positive and becomes stronger for countries that have a sufficiently developed securities market with bias towards middle and high-income countries. On the other hand, this relationship does not seem to hold for low-income countries, as the researchers find no significant causal growth that is spurred by financial development. This finding suggests that low-income countries are not going increase their GDP from financial deepening but rather will benefit from other growth factors; in fact they have not reached a level of optimality that would be necessary to experience the positive finance led economy relationship as described by Law & Singh (2014) and Shen & Lee (2006). Henderson et al. (2013) seem to suggest that low-income countries first need to reach a certain level of economic development before any financial intermediation can be effective in spurring growth. This non-finance growth experienced in less developed countries affirms that the GDP is dependent on a variety of factors and that financial developments is only one among them. This hypothesis, however, is only tested using bank-based variables under the assumption that financial markets are less effective for economic growth in low-income economies (Henderson et al., 2013).

Browner and Ventura (2016) study the case for financial deepening versus capital flight as countries develop financially as measured by the stock exchange activity. Their results also support the inverted-U hypothesis and show that developed countries tend to increase financial depth with increased financial development, but that the case is rather different to developing countries. Developing the financial markets in developing countries tends to increase capital flight instead of increasing financial depth, and as a result, the economy grows much less with financial development compared to the response of a developed economy to a similar financial intervention. Capital flight is a leakage that halts economic growth (Beck et al., 2000), because it is a loss of savings that could be converted into productivity.

2.6. The structure of the financial system

Having described the demand-leading and supply-leading hypotheses, it is important to delve into the question of whether the financial architecture of the economy matters. There are generally two broad views with regards to the financial architecture: namely, the bank-based view and the market-based view (Beck et al., 2000; Hasan et al., 2016; Levine, 2002). The degree to which an economy will either be bank-based or market-based will directly impact the long-term performance of the economy, and this distinction remains part of the core market reform policy as economies become more open and global (Tadesse, 2006).

The bank-based view puts emphasis on three main channels of banking. Firstly, over time, the bank information about managers and the firms forges a client-relationship between the bank and firm, beyond the basic financial information, which is used to improve capital allocation and corporate governance. Secondly, because banks are deposit takers and therefore ultimately manage the intertemporal and liquidity risk through the interbank market, they are able to ensure market liquidity by safeguarding the deposits and savings and thus to enhance investment efficiency and economic growth. Thirdly, banks mobilize capital through deposits and savings to create a large deposit base that enables them to provide and fund long-term assets by using shorter-dated liabilities through the economies of scale that they create (Levine, 2002). It is argued, however, that during the earlier stages of economic liberation, the financial composition may tend to be biased towards a banking-supported financial system and becoming more market-supported as the economy advances (Demir & Hall, 2017).

The market-based view puts more emphasis on the influence that financial markets may have in stimulating economic growth through three main channels. Firstly, financial markets rely on information and how efficient and effective this information can be used to carry out investment decisions (Arestis et al., 2001). Information sharing in turn creates incentives for research firms to improve on their research capabilities to enable profit maximization. This assumption is highlighted in the efficient market hypothesis (EMH), which asserts that stock prices reflect public information but that if the public information is poor, then investors are able to make a profitable trade though a mispriced stock if they have superior research capabilities (Hirshleifer, Li, & Yu, 2015), also referred to as the information feedback function (Tadesse, 2006). The information feedback function supports the efficient market hypothesis, because it assumes that all relevant information is available and revealed to all third parties through public reporting structures. This gives rise to potential investors forming an opinion on the investment as reflected in the way that they price the investment, meaning that the price of the investment is external to the actual firm and is an aggregated opinion that is formed by potential investors (Tadesse, 2006).

Secondly, in financial markets, a poorly-run firm will be exposed to takeovers because investors are mainly interested in the financial performance of the firm (Čihák et al., 2012). Financial markets will therefore improve corporate governance through transparent reporting and linking the compensation of the firm manager to the performance of the firm. Recent studies (e.g., Alexiou & Vogiazas, 2018; Hasan et al., 2016; Michalopoulos, Laeven, & Levine, 2013) show that good governance is key for economic growth because it creates a conducive environment for economic agents to commit themselves in the growth and friendly manner. Through enhanced governance and its successful achievement in aligning the interests of the firm owners and the managers, the principal-agent problem of a firm is reduced substantially (Arestis et al., 2001).

Lastly, financial markets ease risk management (Levine, 2002). Stock markets make the trading assets less risky because of easier exit strategies whilst allowing companies to have access to capital through equity. Heightened risk in an economy leads to banks pushing back from participation through lending, which may cause the economy to slow down, whilst in the financial markets the risk is more easily distributed and may not result in slowed economic growth (Peia & Roszbach, 2013). The combination of the safer assets from the investor's point of view and the access to capital from the companies improves the allocation of capital by reducing the asymmetries between the providers and the users of capital. The trust relationship between investors and companies is essential for economic growth (Arestis et al., 2001).

Banks have sizable balance sheets supporting the current economic drivers and are not able to screen futuristic economic drivers. As a result, they may tend hold back on innovation and instead extract current profits from existing businesses. In contrast, however, the markets are able to diffuse information much more quickly and efficiently. This particular difference between banks and markets is consistent with the endogenous growth theory, as highlighted by Michalopoulos et al. (2013), who make reference to the financial institutions that screened and financed the technological evolution of railroads in the 19th century. The banking industry was not able to fund the innovations that took place within information processing, telecommunications, and biotechnology fields, which emerged in the 1970s and 1980s. Entrepreneurs were therefore stuck with practical ideas but were unbankable, and this funding gap necessitated financial innovation and the emergence of venture capital firms providing technical and managerial advice which positioned them to better screen the entrepreneur. The combination of both technological and financial innovation is key to economic growth, as it improves on the existing screening methods. These findings are consistent with those of (Hsu et al., 2014), who show that whilst the development of equity markets has a positive effect to innovation and economic growth, whilst bank-based financial systems tend to impede on innovation.

Demirgu-kunt & Maksimovic (2000) make their submissions from the perspective of the entrepreneurs' access to finance, and they find that the development of the banking sector relies on firms that are looking for short-term funding. Due to banks' desire to protect themselves against any business risk, they tend to support and finance stock, which turns around in a trading period that self-liquidates. Financial markets, however, tend to support more of the firms which are looking for long-term funding, because investors in financial markets have a long- term view of their return on investments. This state of affairs means that they are both, in fact, necessary institutions for economic growth. This view is consistent to (Arestis et al., 2001), who argue that stock markets and banks can be seen as substitute and complementary sources for corporate financing. When a corporate entity issues new stock for funding, its credit requirements from the bank tend to decline. On the other hand, however, an increase in stock market capitalization may result in an increased volume of bank business, suggesting that countries with sufficiently developed market systems also have an adequately equipped banking system.

Common amongst both the bank and market-based views are some imperfections that hinder the full optimization of either systems. Firstly, there are still high costs of borrowing, from the bank-based view and there is still difficulty in accessing the market, in the perspective of a market-based view (Demir & Hall, 2017). The general costs of borrowing are relatively high in Africa, which sees credit default swap (CDS) spreads priced over 230 basis points (Aizenman, Hutchison, & Jinjarak, 2013). The effect is that the capital does not find itself into profitable projects but rather goes into safer projects which do not have a long-run and sustainable effect on economic development (Demir & Hall, 2017).

The second commonality is that the markets usually have dominant players or counters who become a major part of the index, and who, through their monopoly or oligopoly, earn supernormal profits (Demir & Hall, 2017). As a result, investors are discouraged from holding a contrarian view, because if in an index upswing which is largely dominated by the monopoly counters, contrarians tend to lose out (Hirshleifer et al., 2015).

Lastly, whilst financial markets have developed to such an extent that information is readily available, some financial opportunities are still not known by market participants until the execution stage or a deal is finalised by the transacting parties, showing that the cost of acquiring information has not reduced and in some instances has actually risen (Demir & Hall, 2017).

These imperfections are also noted by Bai et al. (2016) who find that whilst the earnings potential of listed companies has increased, the information publicly available has not increased. This means that uncertainty has increased with financial development and yet informativeness has not increased.

Demir and Hall (2017) use a nonlinear method to investigate whether a dynamism of financial structures for specific countries, namely Germany, the U.S.A, France and Turkey, in response to their stage of economic development. Their findings show that on the financial markets are dynamic and responsive to changes and banks are relatively mute to economic and technological chages. Peia and Roszbach (2015) reach similar conclusions in their study on advanced economies: out of the 22 countries in their sample, only 11 showed causality patterns with stock markets and GDP, and a reversal link exists between bank development measures and GDP. They affirm the arguments put forward by Demir and Hall (2017) that the causality patterns between finance and GDP differ and are dependent on the type of financial development. Market-based development is more likely to cause economic growth largely because of its ability to adapt to change and innovate its systems to suit to change. Bank-based development is more rigid and is not able to adapt quick enough for the change. Furthermore, Demir and Hall (2017) find that there is a threshold effect on economic development by which the relative importance of bank-based view diminishes overtime, whilst that of markets increase.

These findings are consistent with dynamic panel modelling carried out by Law and Singh (2014) which suggests that financial development improves GDP if it remains within a certain optimal level, after which, its impact will turn negative. These findings confirm structural heterogeneity amongst economies showing that a singular policy may not necessarily work across economies, despite a similar level of economic development. The effects may be even more opaque for countries with different levels of economic development.

2.7. Economic composition of countries

Arguments submitted by researchers (such as Alexiou & Vogiazas, 2018; Berkes et al., 2012) pertaining relationship between economic growth and finance being non-linear and therefore non-monotonic seem to pivot on the fact that financial development creates an environment that is favourable to economic growth but such developments have a limit, whereby it ceases to enhance growth. Regarding economies at the lower end of the curve, Henderson et al. (2013) argue that the countries first need to get onto the economic curve before any enhancement from a financial development perspective can foster growth.

The allocation of resources or capital tends to be focused toward riskless investments (Browner & Ventura, 2016), and as the risk increases, the entrepreneur is required to use more of their own savings as opposed to the country's savings because the banks will hold back from risky assets. This behaviour by investors therefore forges the need to investigate the composition of the specific country to verify whether the economy is composed of riskless investments or not. The set country-specific characteristics play a huge role in defining the impact of growth brought about by the financial system.

The literature cited above (Arestis et al., 2001; Demir & Hall, 2017; Demirgu-kunt & Maksimovic, 2000; Law & Singh, 2014; Peia & Roszbach, 2013) are all attempting to unlock which particular form of funding is most appropriate. Funding specifics is the central theme of this research, which takes into account the heterogeneity that exists in financial policy for countries at dissimilar stages of economic development. Developing countries are typically behind the technological curve, and thus their focus is more toward capital accumulation (also termed "investment-based growth"), and on the other hand, developed countries who participate on the technological curve are more incentivized to participate in innovation-based growth (Rioja & Valev, 2014). Investment-based growth is bank-driven, and innovation-based growth is market-driven (Rioja & Valev, 2014). Hsu et al. (2014) go as far as to claim that whilst market-based growth encourages innovation, bank-based growth impedes innovation.

2.7.1. Financial measures

The following section discuses the measures for financial development that are assumed in this research including comparable measures that have been used in other studies. The study further justifies the use of the selected measures as more appropriate and relevant for this study.

2.7.1.1. Bank-based measures

The bank-based system is more or less the traditional form of finance, and it has various measures that are used in unison to control for biases.

- Broad money (M2) which is notes in circulation (M1), short-term deposits, and money market funds. (M2) is then divided by GDP to determine how deep the financial penetration is within the economy. A higher ratio means that there is a poor level of money circulation in the economy, whilst a lower ratio shows more financial depth. A weakness in M2 is its inability to account for the source of the liquidity as it is not all market liquidity that explains the financial profundity. Secondly, it fails to identify where the liquidity has been allocated these resources (Graff & Karmann, 2006). The allocation of these resources could potentially be skewed away from investors or businesses that would in turn contribute to the GDP. The use of M2 also makes it difficult to compare across time and space, because the institutions in the countries are diverse and may be driven by a wide variety of factors (Graff & Karmann, 2006).

- Private Credit Extension, which measures the amount of loans extended by commercial banks and to the businesses and entrepreneurs in the private sector. This measure captures the mobilization of savings and facilitating transactions, indicating the scale at which the banking system is allocating resources to productive use. It fails, however, to show the efficiency of such allocations and to indicate whether risk is adequately managed (Graff & Karmann, 2006). Hence, a countries could have a reasonable allocation in terms of credit extended to business, but it may not necessarily be channelling these resources efficiently; in this case, the growth impact could be muted relative to a country with a smaller credit ratio but with effective resource channelling. Credit is generally biased to supporting that particular country's key or dominant sector (Barclays Africa Group Financial Markets Index, 2017).

2.7.1.2. Stock market development indicators

There are a number of stock market indicators that have been used in previous studies which mainly measure the stock market's integration, size, liquidity, and volatility. Common measures are:

- Stock Market Turnover (SMT), which measures the amount of trading activity in dollar terms versus the total value of the securities exchange. Both the SMC and SMT reflect liquidity. SMT measures the proportion of shares bought and sold on stock exchange compared to the size of the stock market in its entirety. SMT is usually used together with other value-based measures to control for the price effect, which may increase a value-based measure without necessarily increasing trading activity not as a result of lowered transaction costs but purely from speculative price increases (Levine & Zervos, 2008).

- Stock market capitalization (SMC), measures the size of the domestic stock market in its entirety. SMC is measured by taking the prevailing price and multiplying it by the market capitalization of the stock exchange. It is assumed that the SMC is a reasonable gauge of financial development, because the size and growth of the stock market is related to the ability for firms and entrepreneurs to pursue capital for investment opportunities (Levine & Zervos, 2008). SMC, however, does not take into account the concentration or monopoly of businesses within the stock exchange (Federici & Caprioli, 2009). This means that SMC could be sector bias, reflecting an economic boom in a particular sector, which does not yield market development.

CHAPTER 3. Research hypotheses

3.1. Introduction

To ascertain whether financial deepening has any relationship to economic growth, whether one of correlation or of causality, the research objectives are designed to capture the two broad-based channels described in Levine (2002) of the market-based and the bank-based view. In doing so, the objectives align with the arguments put forth by Demir and Hall (2017) that the causality patterns between financial development (FD) and GDP will be different founded on the origin of financial development.

The stock market proxy used is Stock Market Capitalization (SMC), which is calculated as the prevailing prices of listed shares multiplied by their market capitalization. It is a reasonable indicator because stock market size is tends to be an indication of entrepreneurial potential to grow the economy (Levine & Zervos, 2008).

The bank-based proxy used is the Private Credit Extension (PCE), which is a measure of loans made by banks and to the private sector. PCE measures the mobilization of savings and facilitated transactions, indicating the scale at which the banking system is allocating resources to productive use (Graff & Karmann, 2006).

Correlation analysis is tested, to ascertain the strength of the linear association between two variables. The coefficient is a proportion that lies between -1 and +1 only (Wegner, 2017). A coefficient of determination is calculated to measure the amount of variation in the dependent variable (Gross Domestic Product) relative to the variation in the independent variable(s) (Stock Market Capitalization and Private Credit Extension). The coefficient of determination varies between 0 and 1 (Wegner, 2017). The regression model is then tested for significance by applying a 5% ($\alpha = 0.05$) level of significance (Wegner, 2017).

Causality is scientifically difficult to prove as there are numerous assumptions that need to be considered before such a claim can be made. Firstly, all the random variables must be assumed to be stationary, meaning that their statistical properties are constant over time. Secondly their error terms must be assumed to be uncorrelated else they may tend to overestimate the parameters. Lastly, the number of lagged terms have a statistically material influence on the direction of the causal relationship (Gujarati, 2009). Using principles of the Granger causality test Gujarati (2009), GDP is the dependent variable which will be regressed by first its lags up to a point and then would be regressed by the independent variables of either Stock Market Capitalization (SMC) or Private Credit Extension (PCE).

Hypothesis testing of both correlation and causality will follow the basic principle of a two-tailed hypothesis.

For a simple regression:

Equation 1: Simple regression

$Y_i = \beta_0 + \beta_1 X_1 + \varepsilon_i$ (Gujarati, 2009; Wegner, 2017)

Null hypothesis: H_0: $\beta_1 = 0$

Alternate hypothesis: H_1: $\beta_1 \neq 0$

For multiple regression:

Equation 2: Multiple regression

$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_t X_t$ (Gujarati, 2009; Wegner, 2017)

Null hypothesis: $H_0 : \beta_1 = 0 \quad \beta_2 = 0 \quad \beta_3 = 0 \quad \beta_t = 0$

Alternate hypothesis: $H_1 : \beta_1 \neq 0 \quad \beta_2 \neq 0 \quad \beta_3 \neq 0 \quad \beta_t \neq 0$

The regression model's assumptions, including the following, will be tested for reliability.

- The mean of the residuals must be zero.
- A linear relationship exists between the independent and the dependent variables.
- The variance of residuals must be constant across all dependent variables.
- The residuals must be normally distributed for each dependent variable.
- The residuals must be independent of each other.

3.2. Stock market effect

3.2.1. Hypothesis 1a

Can one predict with reasonable accuracy that a correlation exists between a low-level market-based FD ($MBFD_{low}$), as measured through Stock Market Capitalization (SMC), and the Gross Domestic Product (GDP) of the country?

Null hypothesis one (H_01_a): No significant correlation exists between SMC and the GDP of the country.

Alternative hypothesis one (H_11_a): A significant correlation exists between SMC and the GDP of the country.

3.2.2. Hypothesis 1b

Can one predict with reasonable accuracy that a correlation exists between a medium-level market-based FD ($MBFD_{medium}$), as measured through Stock Market Capitalization (SMC), and the GDP of the country?

Null hypothesis one (H_01_b): No significant correlation exists between SMC and the GDP of the country.

Alternative hypothesis one (H_11_b): A significant correlation exists between SMC and the GDP of the country.

3.2.3. Hypothesis 1c

Can one predict with reasonable accuracy that a correlation exists between a high-level market-based FD ($MBFD_{high}$), as measured through Stock Market Capitalization (SMC), and the GDP of the country?

Null hypothesis one (H_01_c): No significant correlation exists between the SMC and the GDP of the country.

Alternative hypothesis one (H_11_c): A significant correlation exists between SMC and the GDP of the country.

3.2.4. Hypothesis 2a

Can one predict with reasonable accuracy that there is a causal relationship between a low-level market-based FD ($MBFD_{low}$), as measured through Stock Market Capitalization (SMC), and the GDP of the country?

Null hypothesis one ($H_0 2_a$): No significant causal relationship between the SMC and the GDP of the country.

Alternative hypothesis one ($H_1 2_a$): A significant causal relationship between SMC and the GDP of the country.

3.2.5. Hypothesis 2b

Can one predict with reasonable accuracy that there is a causal relationship between a medium-level market-based FD ($MBFD_{medium}$), as measured through SMC, and the GDP of the country?

Null hypothesis one ($H_0 2_b$): No significant correlation exists between SMC and the GDP of the country.

Alternative hypothesis one ($H_1 2_b$): A significant correlation exists between SMC and the GDP of the country.

3.2.6. Hypothesis 2c

Can one predict with reasonable accuracy that there is a causal relationship between a high-level market-based FD ($MBFD_{high}$), as measured through Stock Market Capitalization (SMC), and the GDP of the country?

Null hypothesis one ($H_0 2_c$): No significant correlation exists between SMC and the GDP of the country.

Alternative hypothesis one ($H_1 2_c$): A significant correlation exists between SMC and the GDP of the country.

3.3. Bank-based measures

3.3.1. Hypothesis 3a

Can one predict with reasonable accuracy that a correlation exists between a low-level bank-based FD ($BBFD_{low}$), as measured through Private Credit Extension (PCE), and the GDP of the country?

> Null hypothesis two ($H_0 3_a$): No significant correlation exists PCE and the GDP of the country.

> Alternative hypothesis two ($H_1 3_a$): A significant correlation exists between PCE and the GDP of the country.

3.3.2. Hypothesis 3b

Can one predict with reasonable accuracy that a correlation exists between a medium-level bank-based FD ($BBFD_{medium}$),as measured through Private Credit Extension (PCE), and the GDP of the country?

> Null hypothesis two ($H_0 3_b$): No significant correlation exists PCE and the GDP of the country.

> Alternative hypothesis two ($H_1 3_b$): A significant correlation exists between PCE and the GDP of the country.

3.3.3. Hypothesis 3c

Can one predict with reasonable accuracy that a correlation exists between a high-level bank-based FD ($BBFD_{high}$), as measured through Private Credit Extension (PCE), and the GDP of the country?

> Null hypothesis two ($H_0 3_c$): No significant correlation exists between PCE and the GDP of the country.

> Alternative hypothesis two ($H_1 3_c$): A significant correlation exists between PCE and the GDP of the country.

3.3.4. Hypothesis 4a

Can one predict with reasonable accuracy that there is a causal relationship between a low-level bank-based FD ($BBFD_{low}$), as measured through Private Credit Extension (PCE), and the GDP of the country?

Null hypothesis one (H_04_a): No significant causal relationship between PCE and the GDP of the country.

Alternative hypothesis one (H_14_a): A significant causal relationship between PCE and the GDP of the country

3.3.5. Hypothesis 4b

Can one predict with reasonable accuracy that there is a causal relationship between a low-level bank-based FD ($BBFD_{medium}$), as measured through Private Credit Extension (PCE), and the GDP of the country?

Null hypothesis one (H_04_b): No significant correlation exists between PCE and the GDP of the country.

Alternative hypothesis one (H_14_b): A significant correlation exists between PCE and the GDP of the country.

3.3.6. Hypothesis 4c

Can one predict with reasonable accuracy that there is a causal relationship between a low-level bank-based FD ($BBFD_{high}$), as measured through Private Credit Extension (PCE), and the GDP of the country?

Null hypothesis one (H_04_c): No significant correlation exists between the PCE and the GDP of the country.

Alternative hypothesis one (H_14_c): A significant correlation exists between the PCE and the GDP of the country.

CHAPTER 4. Research Methodology

4.1. Introduction

The research methodology is designed to assess the financial development and economic growth nexus between three countries who differ in terms of their level of financial development. These levels are classified into low, medium, and high in terms of their financial level of development. The financial indicators are the Stock Market Capitalization (a market- based variable) and Private Credit Extension (a bank-based variable). The research is designed to test the impact that financial deepening may have on economic growth based on the inverted-U theory (Aghion, Akcigit, & Howitt, 2015; Hasan et al., 2016; Law & Singh, 2014).

The countries identified in this study are Germany, Chile and Kenya, and they are categorized developmentally in the categories of high, medium and low, respectively. The study tests whether their SMC or PCE is sufficient to justify economic growth for the three countries under consideration.

4.2. Research design

The present research seeks to test an existing theory as opposed to generating a new theory, and therefore it is deductive in its approach (Saunders & Lewis, 2012). The research focuses on three countries classified by their financial depth into segments classified as low, medium, and high. The segmentation is based on the existing rankings from the Global Competitiveness Index (GCI) under the 8th pillar of financial market development and the International Monetary Fund's broad-based index of financial development (Schwab, 2018; Svirydzenka, 2016). The GCI rankings are carried out using surveys collected from 133 countries. The 8th pillar of competitiveness, which measures financial market development, is equally weighted between efficiency and trustworthiness and confidence (Schwab, 2018). Details are reported below.

Figure 4: GCI 8th pillar of competitiveness

A. Efficiency	Definition
Financial services meeting business needs	The extent to which products and services provided by the financial sector meet the needs of the business
Affordability of financial services	Taking into account all the financial services including insurance, loans and trade finance, to what extent do costs impede business activity
Financing through local equity market	How vibrant is the Initial Price Offering (IPO) market for bonds and equity
Ease of access to loans	How easy is it for banks to issue loans
Venture capital availability	Do funders support start-up entrepreneurs
B. Trustworthiness and confidence	
Soundness of banks	Are the banks well capitalized and properly regulated
Regulation of securities exchange	Is the stock and capital market well regulated
Legal rights index	The degree to which collateral and bankruptcy laws protect borrowers' and lenders' rights

Source: (Schwab, 2018)

The IMF broad-based index of financial development rankings mainly focus on pillars of depth, access, and efficiency, consistent with recommendations by Čihák, Demirgüç-Kunt, Feyen, & Levine (2012). The two ranking systems separate and clearly define financial development in terms of a bank-based view and a market based-view (Hasan et al., 2016).

Figure 5: IMF broad-based index for financial development

A. Financial Institutions	
Category	Indicator
Depth	Private sector credit to GDP
	Pension fund assets to GDP
	Mutual funds to GDP
	Insurance premiums, life and non-life, to GDP
Access	Bank branches per 100 000 adults
	ATMs per 100,000 adults
Efficiency	Net interest margin
	Lending-deposits spread
	Non-interest income to total income
	Overhead costs to total assets
	Return on assets
	Return on equity
B. Financial Markets	
Depth	Stock market capitalization to GDP
	Stocks traded to GDP
	International debt securities of government to GDP
	Total debt securities of financial corporations to GDP
	Total debt securities of nonfinancial corporations to GDP
Access	Percent of market capitalization outside of top 10 largest companies
	Total number of issuers of debt (domestic and external, nonfinancial and financial corporations)
Efficiency	Stock market turnover ratio (stocks traded to capitalization)

Source: (Svirydzenka, 2016)

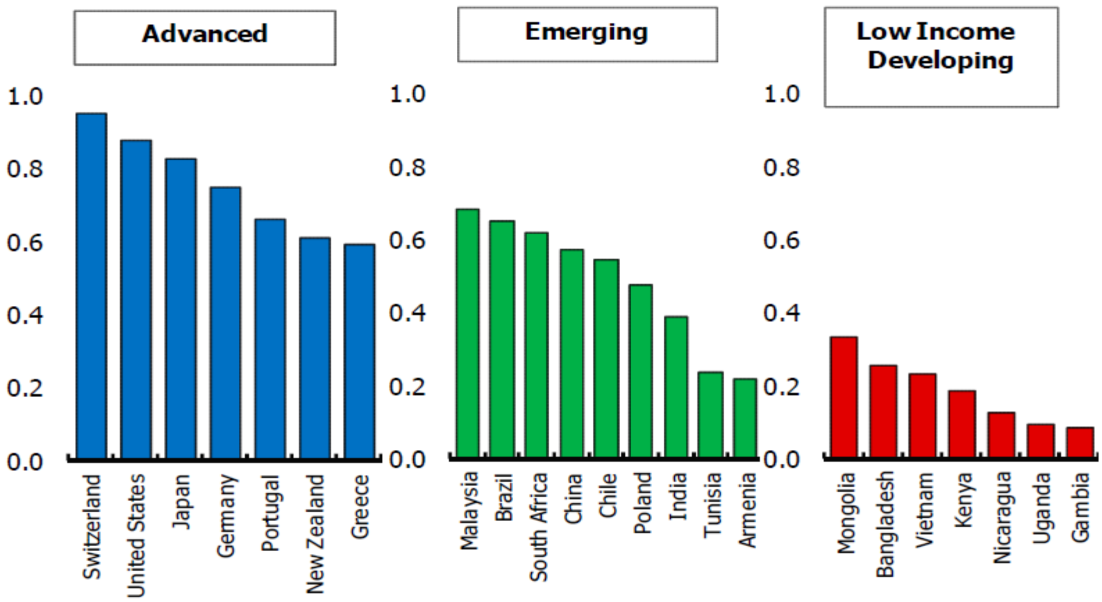
The rankings are categorized into three segments of financial development, namely: high, medium, and low. The preferred measure is the IMF broad-based index for financial development because it measures both the market-based measures and bank-based measures separately. The separation of these two broad financial development measures are core to this study. Finally, the mid-point in each segment is selected as representative of that particular segment (shown in figure 5). The GCI 8^{th} pillar index is used to verify that the classification under the IMF broad-based Index is not dissimilar to the GCI classification.

4.3. Population and sampling

The research focuses on three economically different countries whose level of financial development is determined by taking the average of two independent rankings (Schwab, 2018; Svirydzenka, 2016) to eliminate the effect of possible biases in the ranking methods. This sampling method is a non-probability and purposive sampling technique (Saunders & Lewis, 2012). Purposive sampling is used to select the sample members based reasons determined prior. In this study, selection was made based on the level of financial development which was categorized in three different levels of high, medium and low.

The total number of countries as shown in the World Bank database (2018) is 195. Furthermore, the study considers the ranking data from both the GCI report, which lists 137 countries (Schwab, 2018), and the IMF report, which lists 183 countries (Svirydzenka, 2016). Since the study considered both the reports in their ranking methodology, the sample size was taken as the smaller of the two figures. From the GCI report, the minimum score for financial market development (according to the 8th pillar) is in the region of 20, with the exception of a single country (Mauritania) which was considered as an outlier because it has a score of 2. These rankings were then compared to the IMF broad-based Financial Development Index for consistency. The mid-point of the IMF broad-based Financial Development Index was then used after verifying consistency with the GCI. The median selection is shown in Figure 4.

Figure 6: Financial development index for selected countries



Source: (Svirydzenka, 2016)

4.4. Unit of analysis

The subject of investigation is the correlation and the direction of the correlation as predicted by the Granger causality test (Gujarati, 2009). The units of analysis per experiment are listed below in Figure 4.

Figure 7: Unit of analysis for each of the research tests

Research test	Unit of analysis
Correlation and causality for economic growth—High	Yearly GDP figures for Germany since 1980
Correlation and causality for economic growth— Medium	Yearly GDP figures for Chile since 1980
Correlation and causality for economic growth—Low	Yearly GDP figures for Kenya since 1980
Correlation and causality for SMC—High	Total market value of domestic shares divide by GDP_{deu}
Correlation and causality for SMC — Medium	Total market value of domestic shares divide by GDP_{chi}
Correlation and causality for SMC — Low	Total market value of domestic shares divide by GDP_{ken}
Correlation and causality PCE —High	the loans made by banks to businesses and households to the private sector divide by GDP_{deu}
Correlation and causality for PCE—Medium	the loans made by banks to businesses and households to the private sector divide by GDP_{chi}
Correlation and causality for PCE—Low	the loans made by banks to businesses and households to the private sector divide by GDP_{ken}

Source: Own research

4.5. Data collection process

The analysis of the study covers data from the period 1980 – 2016. The secondary quantitative data is available from the World Bank and the International Monetary Fund electronic databases, the former of which dates back to 1966, and supporting data is taken from the World Federation of Exchanges.

Table 1: Summary of data and observations

Variable	Total observations	Observations removed
GDP_{deu}	46	0
GDP_{chi}	50	0
GDP_{ken}	50	0
SMC_{deu}	41	0
SMC_{chi}	27	0
SMC_{ken}	24	0
PCE_{deu}	46	0
PCE_{chi}	50	0
PCE_{ken}	50	0

Source: Own research

Figure 5 summarises the number of observations used in the analysis. The data did not have any outliers and thus all observations were included.

4.6. Data analysis approach

All statistical data analysis is performed using IBM SPSS Statistics Version 25 and Gretl Version 1.7.1 software packages. Hypothesis testing will follow the basic approach of a two-tailed hypothesis.

4.7. Model estimation techniques

The following section introduces the model estimation techniques that were used in the study which justifies their use and selection. The models have requirements that must be met and fulfilled to justify their use. These requirements are described in the following section.

4.7.1. Correlation

The reliability of the estimate of Y (i.e. the dependent variable) depends on the strength of the relationship between the X and Y variables (where X is the independent variable); this linear strength is determined by the Pearson's correlation coefficient (Wegner, 2017). A coefficient of determination, which measures the proportion of variation in Y that is explained by X, is calculated by taking the square of the Pearson's correlation coefficient. Lastly, the regression model is tested for significance at a 5% ($\alpha = 0.05$) level of significance (Wegner, 2017).

- The null hypothesis is that there is no pairwise correlation in the variables.
    - Reject the null hypothesis if the p-value is less than or equal to $\alpha = 0.05$, and conclude that there is a pairwise correlation of variables at 95% confidence level (Wegner, 2017);
    - Fail to reject the null hypothesis is the p-value is not less than $\alpha = 0.05$, and conclude that the there is no pairwise correlation of variables at a 95% confidence level (Wegner, 2017).

In the context of the research, the study aims to ascertain whether GDP (the dependent variable) has any association with either PCE or SMC (the independent variables). The correlation between GDP and the independent variables PCE and SMC, will assist the study with regards to the hypotheses 1 and 3.

4.7.2. Multivariate linear regression models

Multiple linear regression (MLR) is typically applied in econometrics and it is used to quantify the connection between one dependent variable, and a range of independent variables (Wegner, 2017).

For a simple regression:

Equation 1: $Y_i = \beta_0 + \beta_1 X_1 + \varepsilon_i$ (Gujarati, 2009; Wegner, 2017)

Null hypothesis: H_0: $\beta_1 = 0$

Alternate hypothesis:H_1: $\beta_1 \neq 0$

For multiple regression:

Equation 2: $Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_t X_t$ (Gujarati, 2009; Wegner, 2017)

Null hypothesis: $H_0 : \beta_1 = 0 \;\; \beta_2 = 0 \;\; \beta_3 = 0 \;\; \beta_t = 0$

Alternate hypothesis: $H_1 : \beta_1 \neq 0 \;\; \beta_2 \neq 0 \;\; \beta_3 \neq 0 \;\; \beta_t \neq 0$

Equations 1 and 2 are linear regression models, where Y represents the dependent variable and β are parameters estimated using the least square method, and X represents the independent variable for all t independent variables (Wegner, 2017). MLR is used in both the correlation tests and also in the later VAR tests. For all the tests, the dependent variable will remain the GDP whilst the independent variables will change for the different tests. For the correlation test, the independent variables will be PCE and SMC, whilst for the VAR tests, the independent variables will include lagged variables of both PCE and SMC, as determined by the Akaike Information Criterion (AIC), detailed in 4.8.1.

Conditions that are assumed to have been met with reference to the input data (Gujarati, 2009; Wegner, 2017) include:

- A linear relationship exists between the independent and the dependent variables.
- The mean of the residuals must be zero.
- The variance of residuals must be constant across all dependent variables.
- The residuals must be normally distributed for each dependent variable.
- The residuals must be independent of each other.

4.7.3. Normality

Testing for normality is the most basic problem when approaching both a univariate and multivariate dataset (Hanusz & Tarasińska, 2014; Maddala, 2001). There are various methods for testing normality, among which the Shapiro-Wilk test is considered to be the best (Hanusz & Tarasińska, 2014). The Jarque-Bera test is also popular, but it is only applicable in large samples (Hanusz & Tarasińska, 2014; Maddala, 2001). Should the distribution of the error terms be skewed, then transformation may take the form of Box-Cox logarithmic transformation, whereby the distribution is symmetrized by taking logs (Ferrari & Fumes, 2017).

The Shapiro-Wilk tests were performed using SPSS v. 25.

The null hypothesis is that the data are normally distributed.

We reject the null hypothesis if the p-value is less than or equal to $\alpha = 0.05$, and conclude that the data are not normally distributed at 95% confidence level (Hanusz & Tarasińska, 2014);

we fail to reject the null hypothesis is the p-value is not less than $\alpha = 0.05$, and conclude that the data is normally distributes at a 95% confidence level (Hanusz & Tarasińska, 2014).

4.7.4. Linearity

Linearity is a necessary condition for multiple linear regression and can either be checked and confirmed graphically or computed through an ANOVA (Gujarati, 2009). When checking for linearity using the graphical method, the standardized residuals are plotted against the standardized estimates, and they should show a random pattern (Garson, 2012). In the ANOVA test of linearity, if the F test is significant, then there is non-linearity.

4.7.5. Multicollinearity

In instances where the explanatory variables are highly correlated and have a linear relationship, they are said to be collinear (Ferrari & Fumes, 2017; Gujarati, 2009; Maddala, 2001). Causes of multicollinearity include the use of lagged variables of one another (Samargandi et al., 2015), as well as variables which have a similar trend and capture a similar phenomenon (Law & Singh, 2014).

There are various consequences if the model specified has high collinearity. One consequence is a high R squared, which gives the illusion of a regression that looks good, but the individual explanatory variables are insignificant. The regression may be increasingly sensitive to the addition or removal of explanatory variables which is a sign of high collinearity amongst them (Gujarati, 2009). With high variances, the confidence intervals need to be wide (Gujarati, 2009).

The detection of multicollinearity often does not use formal statistical tests but instead uses two sample measurements as an indication of multicollinearity (Sinan & Alkan, 2015). Firstly, we proceed by inspecting the pairwise correlations from the correlation matrix and correlation coefficients in the region of 0.8 or above signal multicollinearity (Sinan & Alkan, 2015). However, the pairwise correlation coefficient only identify the linear relationship between the two variables (Gujarati, 2009).

Secondly, multicollinearity can be detected using the Variance Inflation Factor (VIF), which can be stated as:

Equation 3: Variance Inflation Factor (VIF)

$$VIF_k = \frac{1}{1 - R_k^2}$$

adapted from (Gujarati, 2009)

VIFs greater than 10 signal a highly likely presence of multicollinearity. This was performed by regressing the independent variables against each other (pairwise).

4.7.6. Homoscedasticity

Homoscedasticity is the assumption that the residuals across all independent variables are consistent, and when plotted graphically do not show a trend but instead a patternless cloud of dots (Gujarati, 2009). There are, however, various reasons as to why the variances of the independent variables may differ over time: these reasons may include error-learning models, improvements in data collection techniques, the presence of outliers, and also skew in the distribution of one or more regressors (Gujarati, 2009).

Whilst the presence of heteroscedasticity in a time series dataset is not uncommon (Louzada, Ferreira, & Diniz, 2014), inferences drawn from the model are likely to be misleading under homoscedasticity because it tends to increase the variances of the coefficients, therefore producing t-values and F-values that appear to be statistically significant although they are not (Gujarati, 2009).

There are a number of tests that can be employed to test for heteroscedasticity, including the Goldfeld-Quandt test, which runs the upper and lower values of the dependent variables and then conducts an F-test on the ratio of the error sum of squares (Gujarati, 2009; Louzada et al., 2014; Zeng, 2016). A less powerful test is White's test, which does not rely on the normality assumptions (Gujarati, 2009) and does not need previous information of the form of heteroscedasticity (Louzada et al., 2014). The Breusch-Pagan test is a specialised case of White's test (Zeng, 2016), and the Koenker test is a modified version of the BP test adjusted for smaller sample sizes (Agbeyegbe, 2015; Reed & Smith, 2017; Zeng, 2016).

The most common test, however, is Levene's test of homogeneity, which tests the assumption that each group independent variables have the same variance (Garson, 2012). Levene's test is intended to be more robust for non-parametric and smaller sample sizes (Nordstokke & Zumbo, 2010). In the present investigation,

Gretl 1.7.1 was used to perform the Breusch-Pagan & White's test

- The null hypothesis is that the data (residuals) are homoscedastic.
  - Reject the null hypothesis if the p-value is less than or equal to $\alpha = 0.05$, and conclude that the residuals are heteroscedastic at 95% confidence level (Zeng, 2016);
  - Fail to reject the null hypothesis is the p-value is not less than $\alpha = 0.05$, and conclude that the residuals are not heteroscedastic but are homoscedastic (Zeng, 2016).

4.7.7. Autocorrelation

Lastly, the residuals of the error terms must be independent of each other such that the expected mean between the error terms is zero (Maddala, 2001; Zeng, 2016). If there is a relationship and therefore a correlation between the error terms, there exists autocorrelation, which is defined as the correlation between members of series of observations ordered in time or space (Gujarati, 2009). A commonly used method to detect serial correlation is the Durbin-Watson test (Gujarati, 2009; Maddala, 2001; Zeng, 2016) which is modelled on the assumption that error terms in the regression model are generated by a first-order autoregressive process.

The Durbin-Watson tests were performed using SPSS v. 25.

- The null hypothesis is that there is serial correlation present.
  - Reject the null hypothesis if the p-value is less than or equal to $\alpha = 0.05$, and conclude that there is a presence of serial correlation in the error terms at 95% confidence level (Zeng, 2016);
  - Fail to reject the null hypothesis if the p-value is not less than $\alpha = 0.05$, and conclude that the data there is no serial correlation in the error terms

at a 95% confidence level (Zeng, 2016).

4.8. Vector autoregressive (VAR) model

Vector Autoregressive (VAR) models are widely used in econometrics for testing variables that are generally not integrated or cointegrated (Konstantakis, Milioti, & Michaelides, 2017; Toda & Yamamoto, 1995). These models are an extension of univariate autoregressions and have maintained their simplicity and flexibility (Escanciano, Lobato, & Zhu, 2013). The VAR framework is used to determine the dynamic relationship between financial development and economic growth, enabling the identification of how the variables of a system co-move (Konstantakis et al., 2017).

Consider a VAR model with only one lag (VAR_1):

Equation 4: Single variable $\mathbf{VAR_1}$ with a single time lag

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \varepsilon_{1t}$$

Adapted from (Maddala, 2001)

VAR_1 has a single lag, where y_t is the economic growth and α is the coefficient of the lagged values of economic growth.

For p-lagged variables,VAR_p:

Equation 5: Single variable VAR_p with p-lags

$$y_t = \alpha_0 + \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \cdots + \alpha_p y_{t-p} + \varepsilon_t$$

Adapted from (Maddala, 2001)

If we consider two economic time series, y_{1t} and y_{2t}, and we assume that y_{1t} is economic growth (as discussed in Equation 5) and y_{2t} is financial growth, then the VAR model with p-lagged variables would be as follows:

Equation 6: VAR model with two variables and p-lags

$$y_{1t} = \alpha_{10} + \alpha_1 y_{1t-1} + \alpha_{12} y_{1t-2} + \cdots + \alpha_{1p} y_{1t-p} + \varepsilon_{1t}$$

$$y_{2t} = \alpha_{20} + \alpha_{21} y_{2t-1} + \alpha_{22} y2_{t-2} + \cdots + \alpha_{2p} y_{2t-p} + \varepsilon_{2t}$$

Adapted from (Maddala, 2001)

In vector form, we can incorporate the simultaneous above in Equation 6:

Equation 7: VAR vector model

$$X_t = \begin{pmatrix} x_{1,t} \\ \vdots \\ x_{n,t} \end{pmatrix}, c =, A_i = \begin{pmatrix} a_{11,i} & \cdots & a_{1n,i} \\ \vdots & \ddots & \vdots \\ a_{n1,i} & \cdots & a_{nn,i} \end{pmatrix}, \varepsilon_t = \begin{pmatrix} \varepsilon_{1,t} \\ \vdots \\ \varepsilon_{n,t} \end{pmatrix}$$

Adapted from (Maddala, 2001)

Alternatively:

Equation 8: Simplified VAR vector model

$$X_t = c + A_1 X_{t-1} + \cdots + A_p X_{t-p} + \varepsilon_t$$

Adapted from (Maddala, 2001)

Wherec_i are the intercepts

$x_{i,t}$ are the endogenous variables *i* at time *t*

$a_{ij,k}$is the impact of variable *j* on variable *i* lagged by *k*

$\varepsilon_{i,t}$ is the residual of *i*

The biggest challenge in VAR modelling is choosing an appropriate lag length (Reed & Smith, 2017). The optimal number of lags can be chosen by using the Akaike Information Criterion (AIC).

4.8.1. The Akaike Information Criterion

The Akaike Information Criterion (AIC) was initially proposed by Hirotugu Akaike in 1971 as a way to compare varying models for a given outcome (Emiliano, Vivanco, & De Menezes, 2014; Ogasawara, 2016). The AIC shows a better model fit for more variables that are included in the model and at the same time penalises the added variables (Emiliano et al., 2014). These two components are the bias factor and the variance factor respectively. The model demonstrates that the bias factor is asymptotically given by the number of variables included in the model (Ogasawara, 2016). Equation 8 below demonstrate the two components of the AIC, showing the bias component, $2log\boldsymbol{\mathcal{L}}\left(\hat{\boldsymbol{\theta}}|\,\boldsymbol{y}\right)$ and the variance component $\boldsymbol{2k}$.

Equation 9: Akaike information criterion (AIC)

$$AIC = -2log\boldsymbol{\mathcal{L}}\left(\hat{\boldsymbol{\theta}}|\,\boldsymbol{y}\right) + \boldsymbol{2k}$$

Adapted from (Emiliano et al., 2014)

4.8.2. Stationarity

Stationarity of time series data refers a property for which the mean and variance are constant over time (Gujarati, 2009), meaning that the variance and mean of the series do not vary systematically over time. Another condition for stationarity is that the value of the covariance of two time periods is only dependent on the lag and not on the time at which the covariance is computed. The importance of stationarity lies with forecasting, because if the series is time-varying, then the model only works for the years period and cannot be used to generalize it to other time periods (Gujarati, 2009). These three conditions are stated below:

Equation 10: Mean for time series data

$$\in (Y_t) = \mu$$

Adapted from (Gujarati, 2009)

Equation 11: Variance for time series data

$$var(Y_t) = \in (Y_t - \mu)^2 = \sigma^2$$

Adapted from (Gujarati, 2009)

Equation 12: Covariance for time series data

$$\gamma k = \in [(Y_t - \mu)\text{^}2(Y_{t+k} - \mu)\text{^}2]$$

Adapted from (Gujarati, 2009)

Unit roots can result in severe statistical difficulties in a regression model if not dealt with: they can result in inconsistent coefficient estimators (Diaz-Emparanza, 2014). Unit root tests vary according to the characteristics of the time series that is being investigated, implying that there are various unit root tests which differ by the variables used and in their methodological approach (Firat, 2016). The reasons behind having numerous unit root tests lies in the size, which is described as the probability of committing a Type I error.

A common unit root tests is the Augmented Dickey-Fuller (ADF) type. It is also more desirable for time series analysis (Reed & Smith, 2017). The ADF is an improvement on the Dickey-Fuller (DF), as the ADF does not assume an uncorrelated error term. (Gujarati, 2009), but it is not reliable to use in the presence of cointegration in the time series (Reed & Smith, 2017).

The Kwiatkowsky, Phillips, Schmidt and Shin (KPSS) test statistic is defined as the ratio of the sum of squared partial sums of the observed series to a long-run variance estimator (Su, Amsler, & Schmidt, 2012). Whilst the KPSS test is widely used in empirical work, the ADF is more reliable and more widely used in series data (Grabarczyk, Wagner, Frondel, & Sommer, 2018; Konstantakis et al., 2017; Shrestha & Bhatta, 2018).

The ADF test was performed using Gretl 1.7.1 software

- The null hypothesis is that the data contains a unit root.
    - Reject the null hypothesis if the p-value is less than or equal to $\alpha = 0.05$, and conclude that the data does not contain a unit root at 95% confidence level (Shrestha & Bhatta, 2018);
    - Fail to reject the null hypothesis is the p-value is not less than $\alpha = 0.05$, and conclude that the data contains a unit root at a 95% confidence level (Shrestha & Bhatta, 2018).

4.8.3. Cointegration

Cointegration arises in time series where there are long-term trends or equilibria between variables (Gujarati, 2009). Cointegration may arise even if the individual variables are non-stationary but the sum of the variables are stationary (Gujarati, 2009; Maddala, 2001). Cointegration may be tested using the ADF unit root test results on the residuals estimated from the cointegration regression or by the cointegration regression Durbin-Watson (CRDW) (Gujarati, 2009). The ADF method for cointegration is called the Augmented Engle-Granger (AEG) test and uses the residuals of the estimated regression using the ADF to test for any cointegration (Maddala, 2001). The CRDW tests for first order autocorrelation and assumes that the model is a random walk (Shen & Lee, 2006). The AEG is preferred over the CRDW, as the CRDW suffers the extreme sensitivity of the model assumption and the AEG has greater power (Browner & Ventura, 2016).

The AEG test was performed using Gretl Version 1.7.1 software.

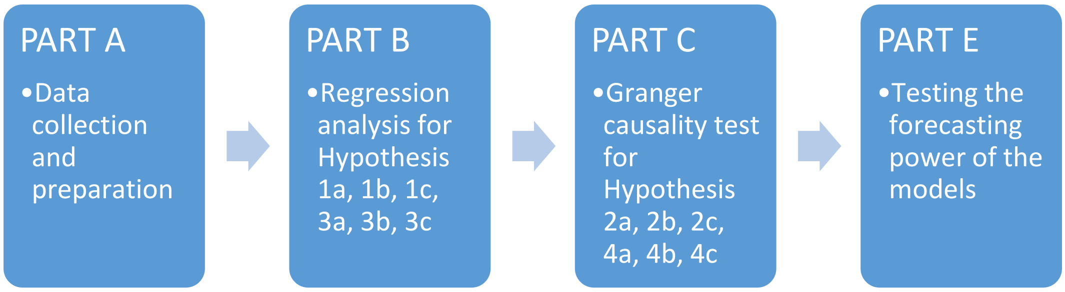
- The null hypothesis is that there is no presence of cointegration in variables.
- Reject the null hypothesis if the p-value is less than or equal to α = 0.05, and conclude that there is cointegration of variables at 95% confidence level (White & Pettenuzzo, 2014);
- Fail to reject the null hypothesis is the p-value is not less than α = 0.05, and conclude that the there is no cointegration of variables at a 95% confidence level (White & Pettenuzzo, 2014).

4.8.4. Causality

Granger (1969) describes a feedback situation whereby lagged values of one variable may be used to determine causality of another variable due to the slowness of recording information. This fundamental hypothesis is founded on the concept of unidirectional causality dimensions, whereby the future value can be shown by historical values but the future value cannot determine past values (Bhattacharjee & Ghosh, 2015). Simply stated, if X causes Y, then the future value Y can be elucidated by the historical values of both X and Y. If, however, the variables are cointegrated, then the overall model is not suitable and would therefore need error-correction models to include the adjustment toward equilibrium (Konstantakis et al., 2017).

4.9. The methodological process

Figure 8: Review of process



Source: Own research

4.9.1. PART A: Data collection and preparation

Data is collected as outlined in Section 4.2. and quality tests are run on the data as highlighted in Section 4.7. The data has not been transformed because the logarithmic transformations did not pass the normality tests. As a result, the data was kept unchanged despite not passing all the quality tests that are highlighted in Section 4.7.

4.9.2. PART B: Regression analysis for testing Hypotheses 1 and 3

Hypotheses 1 and 3 seek to test whether there is any correlation between the dependent variable (GDP) and the independent variables (SMC and PCE). The independent variables are classified as either a market-based factor (stock market capitalization) or a bank-based factor (private credit extension).

The simple linear regression models that will be tested for correlation are;

Equation 13: Simple linear regression for GDP and SMC

$GDP_k = \beta_0 + \beta_k SMC_k$ for the market-based factor and,

Source: Own research

Equation 14: Simple linear regression for GDP and PCE

$GDP_k = \beta_0 + \beta_k PCE_k$ for the bank-based factor;

Source: Own research

Where, *k* is the *k*th country.

Equation 15: MLR for GDP

$$GDP_t = \beta_0 + \beta_1 SMC_t + \beta_2 PCE_t + \varepsilon_t$$

Source: Own research

Where, GDP_t is the economic growth of a country at time, t
SMC is the stock market growth, measured by capitalization
And PCE is the credit growth

4.9.3 PART C: Regression analysis for testing hypotheses 2 and 4

From Equation 6, the VAR equation can be modelled as follows:

Equation 16: VAR model for the current study

$$GDP_{kt} = \alpha_{10} + \alpha_1 GDP_{t-1} + \alpha_1 SMC_{t-1} + \alpha_3 PCE_{t-1} + \varepsilon_{1t}$$

$$SMC_{kt} = \alpha_{20} + \alpha_1 SMC_{t-1} + \alpha_2 GDP_{t-1} + \alpha_3 PCE_{t-1} + \varepsilon_{2t}$$

$$PCE_{kt} = \alpha_{30} + \alpha_1 PCE_{t-1} + \alpha_2 GDP_{t-1} + \alpha_3 SMC_{t-1} + \varepsilon_{3t}$$

Source: Own research

Where GDP_{1t} is the growth output for country *k* at time t,
SMC_{kt} is the market-based growth for country *k* at time t and,
PCE_{kt} is the bank-based growth for country *k* at time t.

The VAR model shows each variable modelled against the other variables including itself, for previous periods. The periods are called lags, and are determined by the The Akaike Information Criterion (AIC) as described in Section 4.8.1. The equations above only show the model for 1 lag i.e. t-1. Only after the AIC test is carried out, will one know the lags recommended for each test.

4.9.4 PART E: Testing the forecasting power of the models

Out of sample testing, of other countries. The classification of the countries by their level of financial development is maintained for consistency.

- A low model based on Kenya can be used to forecast PCE and SMC influence on GDP
- A medium model based on Chile can be used to forecast PCE and SMC influence on GDP
- A high medium model based on Germany can be used to forecast PCE and SMC influence on GDP

CHAPTER 5. Results

5.1. Introduction

This chapter uses variable codes, and the general convention of naming that was applied as follows:

- GDPdeu: Gross Domestic Product of Germany
- GDPchi: Gross Domestic Product of Chile
- GDPken: Gross Domestic Product of Kenya
- SMCdeu: Stock Market Capitalization of Germany
- SMCchi: Stock Market Capitalization of Chile
- SMCken: Stock Market Capitalization of Kenya
- PCEdeu: Private Credit Extension of Germany
- PCEdeu: Private Credit Extension of Chile
- PCEdeu: Private Credit Extension of Kenya

5.2. Descriptive statistics

A full list of descriptive statistics are shown in Appendix 9.2.

5.3. Pre-estimation data quality tests

A full list of detailed pre-estimation data quality tests are shown in Appendix 9.3.- 9.5.

5.3.1. Hypotheses 1a and 2a

5.3.1.1. Test for normality

Table 2: Normality test for hypothesis 1a and 2a

	Shapiro-Wilk			
	Statisitc	df	Sig	Conclusion
GDPken	0.914	50	0.001	Non-normal
SMCken	0.921	24	0.063	normal

Source: Own research

Since the p-value for GDPken (0.001) < pα (0.05), we reject the null hypothesis of normality and conclude that GDPken is non-normal.
Since the p-value for SMCken (0.063) > pα (0.05, we fail to reject the null hypothesis on normality.

5.3.1.2. Test for linearity

Table 3: Linearity for hypothesis 1a and 2a

Model Summary and Parameter Estimates

Dependent Variable: GDPken

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.173	4.609	1	22	.043	854.476	2.216		
Logarithmic	.103	2.515	1	22	.127	819.231	28.323		
Inverse	.033	.741	1	22	.399	913.442	-194.901		
Quadratic	.215	2.868	2	21	.079	893.591	-2.972	.125	
Cubic	.329	3.268	3	20	.043	1012.488	-27.330	1.414	-.020
Compound	.174	4.647	1	22	.042	854.929	1.002		
Power	.100	2.452	1	22	.132	823.914	.030		
S	.030	.672	1	22	.421	6.814	-.201		
Growth	.174	4.647	1	22	.042	6.751	.002		
Exponential	.174	4.647	1	22	.042	854.929	.002		
Logistic	.174	4.647	1	22	.042	.001	.998		

The independent variable is SMCken.

Source: Own research

Since the p-value (0.043) < p-α (0.05), we reject the null hypothesis of non-linearity and conclude that the variables are linear. The scatter plot are shown in Appendix 9.6. which show the linear relationship graphically.

5.3.1.3. Multicollinearity

$$VIF_k = \frac{1}{1 - R_k^2}$$

$VIF_{hypothesis1a}$ = 1.356, and less than 10, indicating that there is no significant multicollinearity present.

5.3.1.4. Homoscedasticity

Table 4: White's test for homoscedasticity - Hypotheses 1a, 2a, 3a and 4a

White's test for heteroskedasticity

OLS, using observations 1989-2014 (T = 26)

Dependent variable: uhat^2

	coefficient	std. error	t-ratio	p-value
const	5532.79	21021.4	0.2632	0.7951
PCEken	205.177	1820.12	0.1127	0.9114
SMCken	−610.311	635.397	−0.9605	0.3483
sq_PCEken	−12.6983	42.6164	−0.2980	0.7688
X2_X3	28.5534	31.1287	0.9173	0.3699
sq_SMCken	−4.40811	10.9412	−0.4029	0.6913

Unadjusted R-squared = 0.144962

Test statistic: TR^2 = 3.769015,

with p-value = P(Chi-square(5) > 3.769015) = 0.583128

Source: Own research

Since the p-value (0.583) > p-value (0.05) we fail to reject the null and conclude that the residuals are not heteroscedastic but are homoscedastic.

Table 5: Breusch-Pagan test for homoscedasticity

Breusch-Pagan test for heteroskedasticity

OLS, using observations 1989-2014 (T = 26)

Dependent variable: scaled uhat^2

	coefficient	std. error	t-ratio	p-value
const	0.0659650	1.42684	0.04623	0.9635
PCEken	0.0763413	0.0660807	1.155	0.2598
SMCken	−0.0462640	0.0293064	−1.579	0.1281

Explained sum of squares = 4.70544

Test statistic: LM = 2.352718,

with p-value = P(Chi-square(2) > 2.352718) = 0.308400

Source: Own research

Since the p-value (0.3084) > p-value (0.05) we fail to reject the null and conclude that the residuals are not heteroscedastic but are homoscedastic.

5.3.1.5. Autocorrelation

Table 6: Autocorrelation - hypotheses 1a and 2a

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.416[a]	.173	.136	55.008788925002804	.173	4.609	1	22	.043	.225

a. Predictors: (Constant), SMCken

b. Dependent Variable: GDPken

Source: Own research

Rejection region

If $d < d_L$ reject $H_0: \rho = 0$

If $d > d_U$ do not reject $H_0: \rho = 0$

If $d_L < d < d_U$ test in inconclusive

For n = 24, *k* = 1 and for $\alpha = 0.05$,

d_L = 1.273 and $d_U = 1.446$

Reject H_0 and conclude that there exists autocorrelation

5.3.2. Hypotheses 1b and 2b

5.3.2.1. Test for normality

Table 7: Normality test - hypotheses 1b and 2b

	Shapiro-Wilk			
	Statisitc	df	Sig	Conclusion
GDPchi	0.866	50	0.00	Non-normal
SMCchi	0.948	27	0.194	normal

Source: Own research

Since the p-value for GDPchi (0.00) < pα (0.05), we reject the null hypothesis of normality and conclude that GDPchi is non-normal.

Since the p-value for SMCchi (0.194) > pα (0.05), we fail to reject the null hypothesis on normality.

5.3.2.2. Test for linearity

Table 8: Linearity test-hypotheses 1b and 2b

Model Summary and Parameter Estimates

Dependent Variable: GDPchl

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.480	23.069	1	25	.000	3794.907	75.222		
Logarithmic	.463	21.580	1	25	.000	-12346.479	5141.149		
Inverse	.388	15.838	1	25	.001	13797.607	-262187.020		
Quadratic	.485	11.307	2	24	.000	2500.343	110.025	-.213	
Cubic	.497	7.560	3	23	.001	6555.778	-85.296	2.440	-.011
Compound	.536	28.925	1	25	.000	4952.317	1.008		
Power	.541	29.441	1	25	.000	830.279	.564		
S	.473	22.448	1	25	.000	9.597	-29.393		
Growth	.536	28.925	1	25	.000	8.508	.008		
Exponential	.536	28.925	1	25	.000	4952.317	.008		
Logistic	.536	28.925	1	25	.000	.000	.992		

The independent variable is SMCchi.

Source: Own research

Since the p-value (0.00) < p-α (0.05), we reject the null hypothesis of non-linearity and conclude that the variables are linear. The scatter plot are shown in Appendix 9.7. which show the linear relationship graphically.

5.3.2.3. Multicollinearity

$$VIF_k = \frac{1}{1 - R_k^2}$$

$VIF_{hypothesis1b}$ = 1.635, and less than 10, indicating that there is no significant multicollinearity present.

5.3.2.4. Homoscedasticity

Table 9: White's test for homoscedasticity – hypotheses 1b, 2b, 3b, and 4b

White's test for heteroskedasticity
OLS, using observations 1989-2015 (T = 27)
Dependent variable: uhat^2

	coefficient	std. error	t-ratio	p-value
const	−463513	1.62834e+06	−0.2847	0.7787
PCEchi	31469.5	51852.3	0.6069	0.5504
SMCchi	−15532.6	16669.1	−0.9318	0.3620
sq_PCEchi	−113.488	312.134	−0.3636	0.7198
X2_X3	−214.289	449.019	−0.4772	0.6381
sq_SMCchi	231.658	213.958	1.083	0.2912

Unadjusted R-squared = 0.278530
Test statistic: TR^2 = 7.520317,
with p-value = P(Chi-square(5) > 7.520317) = 0.184729

Source: Own research

Since the p-value (0.185) > p-value (0.05) we fail to reject the null and conclude that the residuals are not heteroscedastic but are homoscedastic.

Table 10: Breusch-Pagan test for homoscedasticity– hypotheses 1b, 2b, 3b, and 4b

Breusch-Pagan test for heteroskedasticity
OLS, using observations 1989-2015 (T = 27)
Dependent variable: scaled uhat^2

	coefficient	std. error	t-ratio	p-value	
const	−0.360087	1.01742	−0.3539	0.7265	
PCEchi	−0.0183642	0.0159174	−1.154	0.2600	
SMCchi	0.0301590	0.0128367	2.349	0.0274	**

Explained sum of squares = 8.61626
Test statistic: LM = 4.308129,
with p-value = P(Chi-square(2) > 4.308129) = 0.116012

Source: Own research

Since the p-value (0.116) > p-value (0.05) we fail to reject the null and conclude that the residuals are not heteroscedastic but are homoscedastic.

5.3.2.5. Autocorrelation

Table 11: Autocorrelation - hypotheses 1b and 2b

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.693[a]	.480	.459	1921.7350261766280 00	.480	23.069	1	25	.000	.334

a. Predictors: (Constant), SMCchi

b. Dependent Variable: GDPchi

Source: Own research

Rejection region

If $d < d_L$ reject $H_0 : \rho = 0$

If $d > d_U$ do not reject $H_0 : \rho = 0$

If $d_L < d < d_U$ test in inconclusive

For n = 27, k = 1 and for $\alpha = 0.05$,

d_L = 1.316 and d_U = 1.469

Reject H_0 and conclude that there exists autocorrelation

5.3.3. Hypotheses 1c and 2c

5.3.3.1. Normality

Table 12: Normality - hypothesis 1c and 2c

	Shapiro-Wilk			
	Statisitc	df	Sig	Conclusion
GDPdeu	0.949	46	0.044	Non-normal
SMCdeu	0.924	41	0.009	Non-normal

Source: Own research

Since the p-value for GDPdeu (0.044) < pα (0.05), we reject the null hypothesis of normality and conclude that GDPdeu is non-normal.
Since the p-value for SMCdeu (0.009) < pα (0.05), we reject the null hypothesis on normality and conclude that SMCdeu is non-normal.

5.3.3.2. Linearity

Table 13: Linearity - hypothesis 1c and 2c

Model Summary and Parameter Estimates

Dependent Variable: GDPdeu

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.713	96.722	1	39	.000	24108.126	349.272		
Logarithmic	.801	156.665	1	39	.000	4302.129	9414.234		
Inverse	.750	117.000	1	39	.000	43063.675	-171693.914		
Quadratic	.849	106.932	2	38	.000	16236.737	1021.547	-10.489	
Cubic	.857	74.131	3	37	.000	19960.964	532.078	6.096	-.161
Compound	.712	96.596	1	39	.000	24676.308	1.011		
Power	.816	173.377	1	39	.000	13419.794	.288		
S	.782	139.744	1	39	.000	10.694	-5.312		
Growth	.712	96.596	1	39	.000	10.114	.011		
Exponential	.712	96.596	1	39	.000	24676.308	.011		
Logistic	.712	96.596	1	39	.000	4.052E-5	.989		

The independent variable is SMCdeu.

Source: Own research

Since the p-value (0.000) < p-α (0.05), we reject the null hypothesis of non-linearity and conclude that the variables are linear. The scatter plot are shown in Appendix 9.8. which show the linear relationship graphically.

5.3.3.3. Multicollinearity

$$VIF_k = \frac{1}{1 - R_k^2}$$

$VIF_{hypothesis1c}$ = 1.801, and less than 10, indicating that there is no significant multicollinearity present.

5.3.3.4. Homoscedasticity

Table 14: White's test for homoscedasticity – hypotheses 1c, 2c, 3c, and 4c

```
White's test for heteroskedasticity
OLS, using observations 1975-2015 (T = 41)
Dependent variable: uhat^2

              coefficient     std. error    t-ratio  p-value
  ------------------------------------------------------------
  const        2.07792e+08    1.41233e+08   1.471   0.1502
  PCEdeu      −2.91790e+06    3.45677e+06  −0.8441  0.4043
  SMCdeu      −3.00128e+06    1.53919e+06  −1.950   0.0592  *
  sq_PCEdeu    4706.86        21809.9        0.2158  0.8304
  X2_X3        48776.0        24392.7        2.000   0.0534  *
  sq_SMCdeu  −15891.8         15541.2       −1.023   0.3135

  Unadjusted R-squared = 0.381382

Test statistic: TR^2 = 15.636674,
with p-value = P(Chi-square(5) > 15.636674) = 0.007962
```

Source: Own research

Since the p-value (0.008) < p-value (0.05) we to reject the null and conclude that the residuals are heteroscedastic.

Table 15: Breusch-Pagan test for homoscedasticity– hypotheses 1c, 2c, 3c, and 4c

```
Breusch-Pagan test for heteroskedasticity
OLS, using observations 1975-2015 (T = 41)
Dependent variable: scaled uhat^2

             coefficient   std. error   t-ratio   p-value
  ---------------------------------------------------------
  const       2.03697      1.55420       1.311    0.1979
  PCEdeu     −0.0207848    0.0196772    −1.056    0.2975
  SMCdeu      0.0297784    0.0152730     1.950    0.0586  *

  Explained sum of squares = 5.56579

Test statistic: LM = 2.782894,
with p-value = P(Chi-square(2) > 2.782894) = 0.248715
```

Source: Own research

Since the p-value (0.249) > p-value (0.05) we fail to reject the null and conclude that the residuals are not heteroscedastic but are homoscedastic.

5.3.1.5. Autocorrelation

Table 16: Autocorrelation-hypotheses 1c and 2c

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.844[a]	.713	.705	3724.246252253281000	.713	96.722	1	39	.000	.276

a. Predictors: (Constant), SMCdeu

b. Dependent Variable: GDPdeu

Source: Own research

Rejection region

If $d < d_L$ reject $H_0: \rho = 0$

If $d > d_U$ do not reject $H_0: \rho = 0$

If $d_L < d < d_U$ test in inconclusive

For n = 46, *k* = 1 and for $\alpha = 0.05$,

d_L = 1.475 and d_U = 1.566

Reject H_0 and conclude that there exists autocorrelation

5.3.4. Hypotheses 3a and 4a

5.3.4.1. Normality

Table 17: Normality - Hypotheses 3a and 4a

	Shapiro-Wilk			
	Statistic	df	Sig	Conclusion
GDPken	0.914	50	0.001	Non-normal
PCEken	0.969	50	0.217	normal

Source: Own research

Since the p-value for GDPken (0.001) < pα (0.05), we reject the null hypothesis of normality and conclude that GDPken is non-normal.
Since the p-value for PCEken (0.217) > pα (0.05), we fail to reject the null hypothesis of normality.

5.3.4.2. Linearity

Table 18: Linearity - Hypotheses 3a and 4a

Model Summary and Parameter Estimates

Dependent Variable: GDPken

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.686	104.968	1	48	.000	485.630	17.214		
Logarithmic	.712	118.948	1	48	.000	-282.611	374.923		
Inverse	.720	123.246	1	48	.000	1225.425	-7444.502		
Quadratic	.698	54.210	2	47	.000	322.752	32.421	-.334	
Cubic	.786	56.481	3	46	.000	-1265.390	261.701	-10.802	.152
Compound	.660	93.253	1	48	.000	544.094	1.021		
Power	.711	118.078	1	48	.000	211.346	.457		
S	.744	139.348	1	48	.000	7.201	-9.243		
Growth	.660	93.253	1	48	.000	6.299	.021		
Exponential	.660	93.253	1	48	.000	544.094	.021		
Logistic	.660	93.253	1	48	.000	.002	.980		

The independent variable is PCEken.

Source: Own research

Since the p-value (0.00) < p-α (0.05), we reject the null hypothesis of non-linearity and conclude that the variables are linear. The scatter plot are shown in Appendix 9.6. which show the linear relationship graphically.

5.3.4.3. Multicollinearity

$$VIF_k = \frac{1}{1 - R_k^2}$$

$VIF_{hypothesis1b}$ = 1.356, and less than 10, indicating that there is no significant multicollinearity present.

5.3.4.5. Autocorrelation

Table 19: Autocorrelation - Hypotheses 3a and 4a

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.828[a]	.686	.680	64.880339312399230	.686	104.968	1	48	.000	.369

a. Predictors: (Constant), PCEken

b. Dependent Variable: GDPken

Source: Own research

Rejection region

If $d < d_L$	reject $H_0: \rho = 0$
If $d > d_U$	do not reject $H_0: \rho = 0$
If $d_L < d < d_U$	test in inconclusive

For n = 50, k = 1 and for $\alpha = 0.05$,

d_L = 1.503 and $d_U = 1.585$

Reject H_0 and conclude that there exists autocorrelation

5.3.5. Hypotheses 3b and 4b

5.3.5.1. Normality

Table 20: Normality - hypotheses 3b and 4b

	Shapiro-Wilk			
	Statistic	df	Sig	Conclusion
GDPchi	0.866	50	0.00	Non-normal
PCEchi	0.931	50	0.006	Non-normal

Source: Own research

Since the p-value for GDPchi (0.01) < pα (0.05), we reject the null hypothesis of normality and conclude that GDPchi is non-normal.

Since the p-value for PCEchi (0.006) < pα (0.05), we reject the null hypothesis of normality and conclude that PCEchi is non-normal.

5.3.5.2. Linearity

Table 21: Linearity - hypotheses 3b and 4b

Model Summary and Parameter Estimates

Dependent Variable: GDPchl

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.816	212.568	1	48	.000	2581.211	103.414		
Logarithmic	.562	61.555	1	48	.000	-1453.936	2588.386		
Inverse	.300	20.554	1	48	.000	9159.603	-26485.991		
Quadratic	.874	162.977	2	47	.000	3915.821	15.519	.887	
Cubic	.897	133.886	3	46	.000	5230.222	-175.631	5.455	-.028
Compound	.820	218.366	1	48	.000	3593.799	1.013		
Power	.627	80.632	1	48	.000	2006.878	.351		
S	.362	27.266	1	48	.000	9.051	-3.737		
Growth	.820	218.366	1	48	.000	8.187	.013		
Exponential	.820	218.366	1	48	.000	3593.799	.013		
Logistic	.820	218.366	1	48	.000	.000	.987		

The independent variable is PCEchi.

Source: Own research

Since the p-value (0.000) < p-α (0.05), we reject the null hypothesis of non-linearity and conclude that the variables are linear. The scatter plot are shown in Appendix 9.7. which show the linear relationship graphically.

5.3.5.3. Multicollinearity

$$VIF_k = \frac{1}{1 - R_k^2}$$

$VIF_{hypothesis1b}$ = 1.635, and less than 10, indicating that there is no significant multicollinearity present.

5.3.5.4. Autocorrelation

Table 22: Autocorrelation - hypotheses 3b and 4b

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.903[a]	.816	.812	1546.2419870190695 00	.816	212.568	1	48	.000	.121

a. Predictors: (Constant), PCEchi

b. Dependent Variable: GDPchl

Source: Own research

Rejection region

If $d < d_L$ reject $H_0: \rho = 0$

If $d > d_U$ do not reject $H_0: \rho = 0$

If $d_L < d < d_U$ test in inconclusive

For n = 50, k = 1 and for $\alpha = 0.05$,

d_L = 1.503 and d_U = 1.585

Reject H_0 and conclude that there exists an autocorrelation

5.3.6. Hypotheses 3c and 4c

5.3.6.1. Normality

Table 23: Normality - hypotheses 3c and 4c

	Shapiro-Wilk			
	Statisitc	df	Sig	Conclusion
GDPdeu	0.949	46	0.044	Non-normal
PCEdeu	0.966	50	0.163	normal

Source: Own research

Since the p-value for GDPdeu (0.044) < pα (0.05), we reject the null hypothesis of normality and conclude that GDPdeu is non-normal.
Since the p-value for PCEdeu (0.163) > pα (0.05), we fail to reject the null hypothesis of normality.

5.3.6.2. Linearity

Table 24: Linearity - hypotheses 3c and 4c

Model Summary and Parameter Estimates

Dependent Variable: GDPdeu

	Model Summary					Parameter Estimates			
Equation	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.392	28.362	1	44	.000	3013.522	335.238		
Logarithmic	.423	32.278	1	44	.000	-104891.327	30775.273		
Inverse	.449	35.927	1	44	.000	64321.250	-2729114.416		
Quadratic	.487	20.376	2	43	.000	-84255.817	2317.739	-10.976	
Cubic	.487	20.376	2	43	.000	-84255.817	2317.739	-10.976	.000
Compound	.463	37.887	1	44	.000	11329.704	1.012		
Power	.501	44.261	1	44	.000	264.990	1.071		
S	.535	50.584	1	44	.000	11.468	-95.120		
Growth	.463	37.887	1	44	.000	9.335	.012		
Exponential	.463	37.887	1	44	.000	11329.704	.012		
Logistic	.463	37.887	1	44	.000	8.826E-5	.988		

The independent variable is PCEdeu.

Source: Own research

Since the p-value (0.000) < p-α (0.05), we reject the null hypothesis of non-linearity and conclude that the variables are linear. The scatter plot are shown in Appendix 9.8. which show the linear relationship graphically.

5.3.6.3. Multicollinearity

$$VIF_k = \frac{1}{1 - R_k^2}$$

$VIF_{hypothesis1b}$ = 1.801, and less than 10, indicating that there is no significant multicollinearity present.

5.3.6.4. Autocorrelation

Table 25: Autocorrelation - Hypotheses 3c and 4c

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.626[a]	.392	.378	6084.695043300947000	.392	28.362	1	44	.000	.065

a. Predictors: (Constant), PCEdeu

b. Dependent Variable: GDPdeu

Source: Own research

Rejection region

If $d < d_L$ reject $H_0: \rho = 0$

If $d > d_U$ do not reject $H_0: \rho = 0$

If $d_L < d < d_U$ test in inconclusive

For n = 46, k = 1 and for $\alpha = 0.05$,

d_L = 1.475 and d_U = 1.566

Reject H_0 and conclude that there exists autocorrelation

5.3.7. Stationary test for all variables

Table 26: Stationarity test for all variables

Variable code	*ADF test*
GDPken	Non-stationary
GDPchi	Non-stationary
GDPdeu	stationary
SMCken	Non-stationary
SMCchi	Non-stationary
SMCdeu	Non-stationary
PCEken	Non-stationary
PCEchi	stationary
PCEdeu	Non-stationary

Source: Own reseach

Data for all the hypotheses were tested for stationarity in accordance with 4.8.2. The detailed results shown in section 9.4.

5.4. Cointegration

Table 27: Cointegration results

Model	AEG p-value	conclusion
GDPken	0.8891	No cointegration
GDPchi	0.0635	No cointegration
GDPdeu	0.1809	No cointegration

Source: Own research

Since all the p-values of the regression model are less than p-α (0.05), we reject the null hypothesis and conclude that no cointegration of variables is present at a 95% confidence. Detailed results of the Engle-Granger test are shown in Appendix 9.5.1.-9.5.3.

5.5. Data transformation

The data has failed numerous tests and an attempt to transform the data is shown in Appendix 9.6. The results show that autocorrelation is still present for GDPchi reression despite the transformation. The DW statistic is 0.67 which shows the presence of autocorrelation. As a result, it was concluded that the data would fail pre-quality tests because of the relatively small sample sizes. No further transformations were carried out.

5.6. Model estimation

An MLR was calculated to predict the GDP for the various countries of different levels of development.

MLR is typically used in econometrics and it is used to quantify the relationship between one dependent variable, and a range of independent variables (Wegner, 2017).

5.4.1. Low level of economic development

Kenya was used as a proxy to make generalizations about countries of low economic development as summarized in the both the GCI and the IMF broad-based index for financial development (Schwab, 2018; Svirydzenka, 2016).

We consider Equation 2:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

$$GDP_{ken} = 717.878 + 6.855\ (PCE_{ken}) + 0.755\ (SMC_{ken})$$

The model is statistically significant at a 95% confidence since the p-value (0.006) < α (0.05).

The individual IVs however, only show that PCEken is statistically significant at a 95% confidence since the p-value (0.014) < α (0.05) and; SMCken is not statistically significant at a 95% confidence since the p-value (0.485) > α (0.05).

Table 28: GDPken multiple linear regression

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	

1	.620[a]	.385	.326	48.56909 81501694 74	.385	6.567	2	21	.006	.274

a. Predictors: (Constant), SMCken, PCEken

b. Dependent Variable: GDPken

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients			95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta	t	Sig.	Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	717.878	54.890		13.079	.000	603.729	832.027		
	PCEken	6.855	2.551	.536	2.687	.014	1.550	12.159	.737	1.356
	SMCken	.755	1.061	.142	.711	.485	-1.452	2.962	.737	1.356

a. Dependent Variable: GDPken

Source: Own research

5.4.2. Medium level of economic development

Chile was used as a proxy to make generalizations about countries of medium economic development as summarized in the both the GCI and the IMF broad-based index for financial development (Schwab, 2018; Svirydzenka, 2016).
We consider Equation 2:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

$$GDP_{chi} = 596.616 + 118.200\ (PCE_{chi}) + 15.822\ (SMC_{chi})$$

The model is statistically significant at a 95% confidence since the p-value (0.000) < α (0.05).

The individual IVs are both statistically significant at a 95% confidence since the PCE_{chi} p-value (0.000) < α (0.05) and; SMC_{chi} is statistically significant at a 95% confidence since the p-value (0.018) < α (0.05).

Table 29: GDPchi multiple linear regression

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics					Durbin-Watson
					R Square Change	F Change	df1	df2	Sig. F Change	
1	.975[a]	.951	.947	599.880191487074200	.951	234.658	2	24	.000	.593

a. Predictors: (Constant), SMCchil, PCEchi

b. Dependent Variable: GDPchl

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B		Collinearity Statistics	
		B	Std. Error	Beta			Lower Bound	Upper Bound	Tolerance	VIF
1	(Constant)	596.616	495.421		1.204	.240	-425.883	1619.115		
	PCEchi	118.200	7.751	.878	15.250	.000	102.204	134.197	.612	1.635
	SMCchil	15.822	6.251	.146	2.531	.018	2.921	28.723	.612	1.635

a. Dependent Variable: GDPchl

Source: Own research

5.4.3. High level of economic development

Germany was used as a proxy to make generalizations about countries of high economic development as summarized in the both the GCI and the IMF broad-based index for financial development (Schwab, 2018; Svirydzenka, 2016).

We consider Equation 2:

$$Y_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

$$GDP_{deui} = 30936.91 - 89.182\ (PCE_{deu}) + 395.394\ (SMC_{deui})$$

The model is statistically significant at a 95% confidence since the p-value (0.000) < α (0.05).

The individual IVs however on show statistical significance for SMC_{deu} and not for PCE_{deu}.

Since PCE_{deu} p-value (0.149) >α (0.05) it is not statistically significant at a 95% and; SMC_{deu} is statistically significant at a 95% confidence since the p-value (0.000) < α (0.05).

Table 30: GDPdeu multiple linear regression

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.853[a]	.728	.714	3669.672141885127500	.728	50.894	2	38	.000	.354

a. Predictors: (Constant), SMCdeu, PCEdeu

b. Dependent Variable: GDPdeu

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.	95.0% Confidence Interval for B: Lower Bound	Upper Bound	Collinearity Statistics: Tolerance	VIF
1	(Constant)	30936.919	4782.544		6.469	.000	21255.166	40618.672		
	PCEdeu	-89.182	60.560	-.167	-1.473	.149	-211.779	33.415	.555	1.801
	SMCdeu	395.394	46.963	.956	8.419	.000	300.323	490.465	.555	1.801

a. Dependent Variable: GDPdeu

Source: Own research

5.7. Correlations

5.7.1. Correlation for hypothesis 1a

Table 31: Correlation - hypothesis 1a

Table 1

Summary of correlations for Hypothesis 1a

Correlations

		GDPken	SMCken
GDPken	Pearson Correlation	1	.416*

	Sig. (2-tailed)		.043
	N	50	24
SMCken	Pearson Correlation	.416*	1
	Sig. (2-tailed)	.043	
	N	24	24

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Source: own research

The Pearson's correlation was run for the period 1966–2015 in order to assess the relationship between the GDPken and SMCken. The correlation is weak, $r = 0.416$, but since $p < 0.05$, the correlation is statistically significant at a 95% confidence. With SMCken explaining 17% (r^2) of the variation in GDPken, SMCken has a weak positive relationship with GDPken.

5.7.2. Correlation for hypothesis 1b

Table 32: Correlation for hypothesis 1b

Summary of correlations for Hypothesis 1b

Correlations

		GDPchl	SMCchil
GDPchl	Pearson Correlation	1	.693**
	Sig. (2-tailed)		.000
	N	50	27
SMCchil	Pearson Correlation	.693**	1
	Sig. (2-tailed)	.000	
	N	27	27

**. Correlation is significant at the 0.01 level (2-tailed).

Source: own research

The Pearson's correlation was run for the period 1966–2015 in order to assess the relationship between the GDPchi and SMCchi. The correlation is strong, $r = 0.693$, and $p < 0.05$, the correlation is statistically significant at a 95% confidence. With SMCchi explaining 48% (r^2) of the variation in GDPchi. SMCchi has a strong and positive relationship with GDPchi.

5.7.3. Correlation for hypothesis 1c

Table 33: Correlation for hypothesis 1c

Table 3

Summary of correlations for Hypothesis 1c

Correlations

		GDPdeu	SMCdeu
GDPdeu	Pearson Correlation	1	.844**
	Sig. (2-tailed)		.000
	N	46	41
SMCdeu	Pearson Correlation	.844**	1
	Sig. (2-tailed)	.000	
	N	41	41

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Own research

The Pearson's correlation was run for the period 1966–2015 in order to assess the relationship between the GDPdeu and SMCdeu. The correlation is very strong, $r = 0.844$, and $p < 0.05$, the correlation is statistically significant at a 95% confidence. With SMCdeu explaining 71% (r^2) of the variation in GDPdeu, SMCdeu has a strong positive relationship with GDPdeu.

5.7.4. Correlation for hypothesis 3a

Table 34: Correlation for hypothesis 3a

Table 4

Summary of correlations for Hypothesis 3a

Correlations

		GDPken	PCEken
GDPken	Pearson Correlation	1	.828**
	Sig. (2-tailed)		.000
	N	50	50
PCEken	Pearson Correlation	.828**	1
	Sig. (2-tailed)	.000	
	N	50	50

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).
Source: Own research

The Pearson's correlation was run for the period 1966–2015 in order to assess the relationship between the GDPken and PCEken. The correlation is strong, $r = 0.828$, and since $p < 0.05$, the correlation is statistically significant at a 95% confidence. With PCEken explaining 69% (r^2) of the variation in GDPken, PCEken has a strong positive relationship with GDPken.

5.7.5 Correlation for hypothesis 3b

Table 35: Correlation for hypothesis 3b

Summary of correlations for Hypothesis 3b

Correlations

		GDPchl	PCEchi
GDPchl	Pearson Correlation	1	.903**
	Sig. (2-tailed)		.000
	N	50	50
PCEchi	Pearson Correlation	.903**	1
	Sig. (2-tailed)	.000	
	N	50	50

**. Correlation is significant at the 0.01 level (2-tailed).
Source: Own research

The Pearson's correlation was run for the period 1966–2015 in order to assess the relationship between the GDPchi and SMCchi. The correlation is very strong, $r = 0.903$, and $p < 0.05$, the correlation is statistically significant at a 95% confidence. With PCEchi explaining 82% (r^2) of the variation in GDPchi. PCEchi has a very strong and positive relationship with PCEchi.

5.7.6 Testing hypothesis 3c

Table 36: Testing hypothesis 3c

Summary of correlations for Hypothesis 3c

Correlations

		GDPdeu	PCEdeu
GDPdeu	Pearson Correlation	1	.626**
	Sig. (2-tailed)		.000
	N	46	46
PCEdeu	Pearson Correlation	.626**	1
	Sig. (2-tailed)	.000	
	N	46	50

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Own research

The Pearson's correlation was run for the period 1966–2015 in order to assess the relationship between the GDPdeu and PCEdeu. The correlation is very strong, $r = 0.626$, and $p < 0.05$, the correlation is statistically significant at a 95% confidence. With PCEdeu explaining 39% (r^2) of the variation in GDPdeu, PCEdeu has a moderate positive relationship with GDPdeu.

5.8. Granger causality

5.8.1. Granger causality for hypotheses 2a and 4a

Table 37: Vector auto regression for hypotheses 2a and 4a

Independent Variable	Direction and result	Dependent variable
SMCken	Positive and significant	GDPken
PCEken	Not significant	GDPken
GDPken	Not significant	SMCken
GDPken	Not significant	PCEken

Source: Own research

The detailed VAR results are shown in the appendix 9.4.1. The results show that there is a one-way causality of SMCken to GDPken. The coefficient is positive indicating that improvements in the market-based measure causes a positive shock in GDPken.

There is no significant relationship between PCEken and GDPken.

5.8.2. Granger causality for hypotheses 2b and 4b

Table 38: Vector auto regression for hypotheses 2b and 4b

Independent Variable	Direction and result	Dependent variable
SMCchi	Positive and significant	GDPchi
PCEchi	Not significant	GDPchi
GDP_2chi	Positive and significant	SMCchi
GDPchi	Not significant	PCEchi

Source: Own research

The detailed VAR results are shown in the appendix 9.4.2. The results show that there is SMCchi causality to GDPchi, which is positive. This means that development in the market-based measure, results in a positive shock in GDPchi.

PCEchi is not a significant factor in the growth of GDPchi. There seems to be a reverse causality of GDP_2chi on SMCchi showing that as GDPchi grows there also tends to be improvements in SMCchi.

5.8.3. Granger causality for hypotheses 2c and 4c

Table 39: Vector auto regression for hypotheses 2c and 4c

Independent Variable	Direction and result	Dependent variable
SMCdeu	Positive and significant	GDPdeu
PCEdeu	Not significant	GDPdeu
GDPdeu	Not significant	SMCdeu
GDPdeu	Negative and significant	PCEdeu

Source: Own research

The detailed VAR results are shown in the appendix 9.4.3. The results show that there is SMCdeau causality to GDPdeu, which is positive. This means that development in the market-based measure, results in a positive shock in GDPdeu.

There is no significant causal relationship of PCEdeu on GDPdeu but the results show a negative causal relationship of GDPdeu on PCEdeu.

CHAPTER 6. Discussion of results

6.1. Introduction

This chapter attempts to link the results obtained in Chapter 5 with the literature that is discussed in Chapter 2. This is done to test whether the results have any economic foundation that can assist in reaching a reliable conclusion. The overarching theme explored in Chapter 2 is whether there is any relationship between financial development and economic growth. Hence, we seek to prove whether the economy is in fact driven by financial deepening, mainly looking at two sets of financial proxies, one being market-driven and the other being bank-driven. Lastly, we considered whether the level of economic development matters in this nexus of finance and economic growth. All these assumptions, which are based on economic theory and evidence from literature, are tested in their respective hypotheses as described in 3.2. and 3.3.

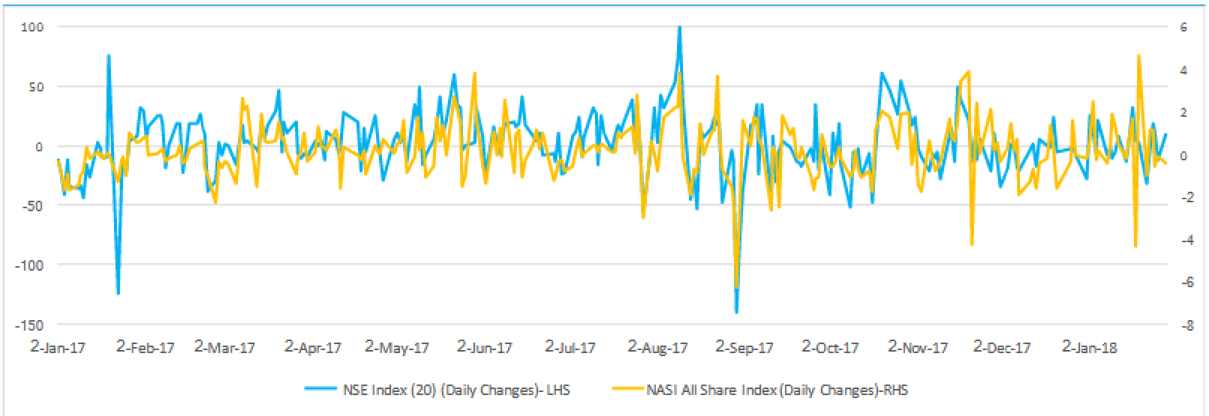
The results are ordered and grouped by variable, and not necessarily by the type of test as in Chapter 5. We will discuss both PCE and SMC in terms of its correlation test and the VAR test.

6.2. Hypotheses 1a and 2a (SMC_{ken})

The results from the linear regression show that the model is statistically significant at a 95% confidence level. SMC_{ken} alone, however, is not significant. This finding supports the arguments put forward by Law & Singh (2014) suggesting that more is required for low-income countries to grow and that this growth may not come from financial deepening but rather from other socio-economic factors.

The results of the correlation between SMC_{ken} and GDP_{ken} are consistent with the results of Law & Singh (2014), which show a positive but weak correlation that is statistically significant. The securities market in Kenya is the most developed in the East African region (Nyasha & Odhiambo, 2017) with both local and foreign investors participating actively. The foreign investors dominate the market and make up 65% of trade participation (Financial Sector Regulators Forum, 2018). In 2017, the Nairobi Securities Exchange recorded a net outflow by foreign investors in the amount of KSh11.58 billion. The results of weak correlation and an insignificant SMC coefficient could suggest that despite the NSE being developed, it is relatively mute regarding any particular contribution to GDP, and the investor outflows could be a plausible explanation. This conclusion was also suggested by Browner & Ventura (2016) who find that in less developed countries, the financial markets tend to increase capital flight as investors are able to liquidate out of perceived risk.

Figure 9: NSE market volatility



Source (Financial Sector Regulators Forum, 2018)

The NSE has troughs and peaks in close proximity with a downward bias, which would explain the net outflow of investment made by foreigners towards the end of Q3 and Q4.

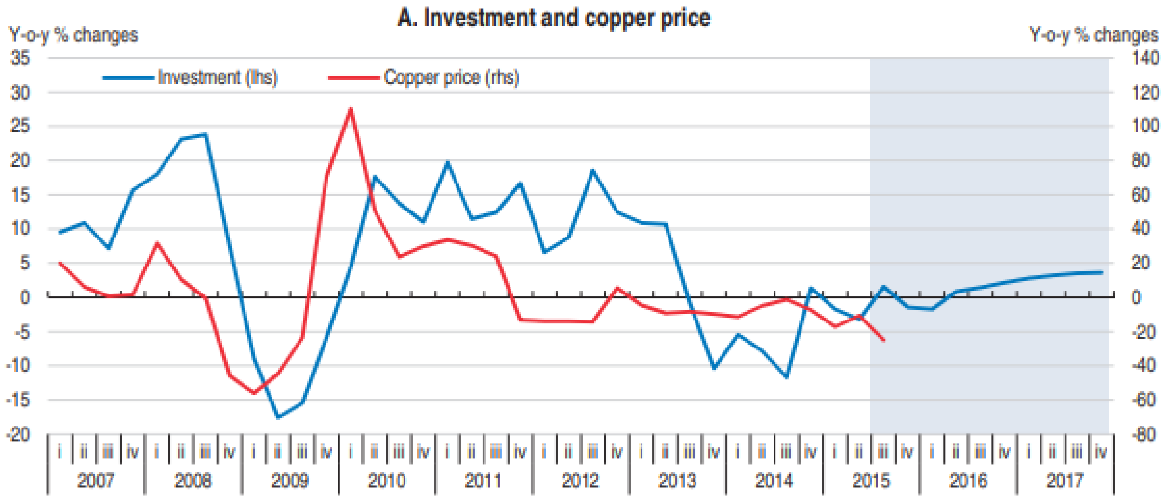
Despite the high foreign-owned portfolio in the NSE, who tend to divest in heightened uncertainty, there is evidence of SMC_{ken} exerting causality on GDP_{ken}. A market-based growth economy is focused on innovation (Rioja & Valev, 2014). Kenya has increased its investment into tech industries after developing its first tech cluster in 2010 (T. Kelly & Firestone, 2016), but even with the increased innovation, Kenya still lacks certain regulations and enforceability of best practices, and hence the multiplier effect of innovation-based growth is weakened.

6.3. Hypotheses 1b and 2b (SMC_{chi})

The results from the linear regression show that the model is statistically significant at a 95% confidence level. Both the SMC_{chi} and the PCE_{chi} are individually significant as well. Henderson et al. (2013) explores the notion of the inverted-U hypothesis and finds that the relationship between finance and GDP is stronger for middle-income countries relative to less developed countries. This evidence is consistent with the results of the present study, which show an increasing SMC_{chi} coefficient relative to SMC_{ken}, meaning that the stock market plays a contributory role in the economic development of Chile.

The correlation between SMC_{chi} and GDP_{chi} is statistically significant, and SMC_{chi} explains 48% of the variation in GDP. This figure is significantly higher than in hypothesis 1b, which is consistent with the notion that the securities markets' role increases with economic development because the level of sophistication increases (Henderson et al., 2013).

Figure 10: Investments in Chile and the fall in copper demand

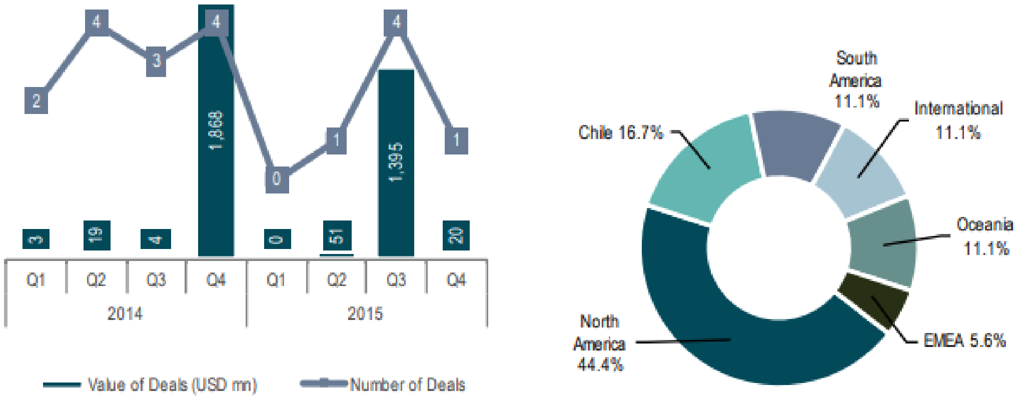


Source: (OECD, 2015)

The graph shows a high correlation of the amount of investments in Chile and the world copper prices. This relationship illustrates the high dependency that the Chile economy and by deduction, the stock exchange as well. The economy is, through copper price volatility, is excessively exposed to market volatility and there tends to be crowding-out of the non-resource sector (OECD, 2015). The copper dependent market could explain the causality of SMC_{chi} to GDP_{chi}.

Similarly, the results also show elements of the demand-following hypothesis, which advocates that the demand for financial services are as a result of firms and entrepreneurs demanding more services as they expand (Liu, 2003).

Figure 11: Number and value of M&A in the Chile mining sector and origin of investor



Source: (EMIS, 2017)

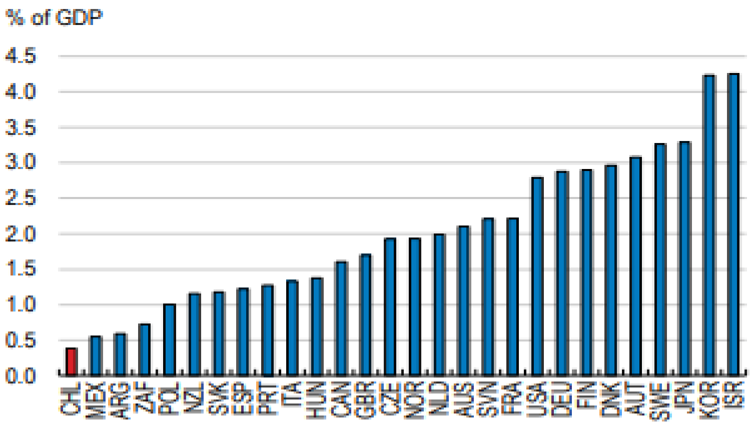
The mining sector in Chile is vibrant and experiences frequent mergers and acquisitions. It is an industry which may drive financial development in the country, as investors may require specific clauses and rights that exist in their country of origin but not necessarily in Chile. This activity would inturn drive financial development.

6.4. Hypotheses 1c and 2c (SMC_{deu})

The results from the linear regression show that the model is statistically significant at a 95% confidence level. PCE_{deu} alone, however, is not significant. The correlation is even stronger than SMC_{chi} (explaining 71% of the variation in GDP_{deu}), showing that the contribution to economic growth shifts more towards the securities markets and away from bank-based measures. The shift towards financial markets was highlighted by Michalopoulos et al. (2013), who observed that banks are not innovative enough to support a sophisticated and dynamic economy.

The causality tests show a positive and statistically significant relationship. This is consistent with the notion that high-income countries are innovation driven and that particular innovation is better supported by markets as opposed to banks (Rioja & Valev, 2014). The graph below illustrates the gross expenditure on R&D as a percentage of GDP for 2015. The high-income countries (including Germany) are concentrated on the RHS, showing high spending in R&D, whilst the relatively lower-income countries are concentrated on the LHS, showing low spending on R&D.

Figure 12: Gross expenditure on R&D as a percentage of GDP, 2015

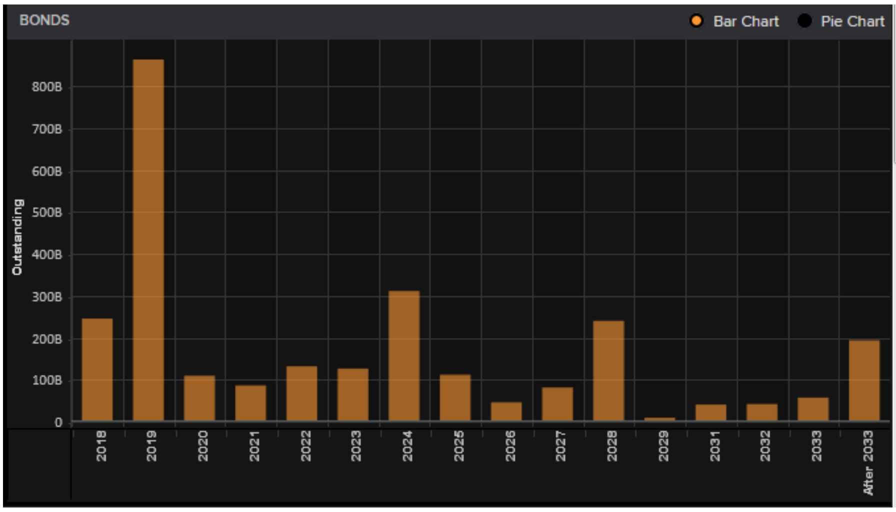


Source: (OECD Chile, 2018)

6.5. Hypotheses 3a and 4a (PCE_{ken})

The results from the linear regression show that the model is statistically significant at a 95% confidence level. PCE_{ken} has a statistically significant coefficient, supporting the fact that low-income economies rely more on bank-based growth as opposed to market-based growth (Samargandi et al., 2015). This claim is also supported by the correlation results, which show a high correlation coefficient of 0.8 (which is statistically significant. PCE_{ken} explains 69% of the variation in GDP_{ken}. The results are consistent with findings from researchers such as Berkes et al. (2012) and Henderson et al. (2013), who suggest that low-income countries first develop through bank-based measures up to a point where banks can no longer support new innovative projects. Demirgu-kunt & Maksimovic (2000) further state that banks are generally short-term funders who de-risk themselves from participating in longer-term asset transactions. In the absence of participation in long-term activities, the markets tend to be short-term, i.e. based only on participation in the shorter end of the yield curve.

Figure 13: NSE bond market maturity profile



Source: (Thomson Reuters, 2018)

The maturity bar graph for government securities in Kenya illustrate the short-term ability for government to borrow. The likelihood therefore is that in the credit market of the bank-based measure (PCE), the loans extended to customers are mostly short-tem in nature. This supports the notion by (Demirgu-kunt & Maksimovic, 2000) that credit markets are used mainly for supporting projects which are short-term in nature.

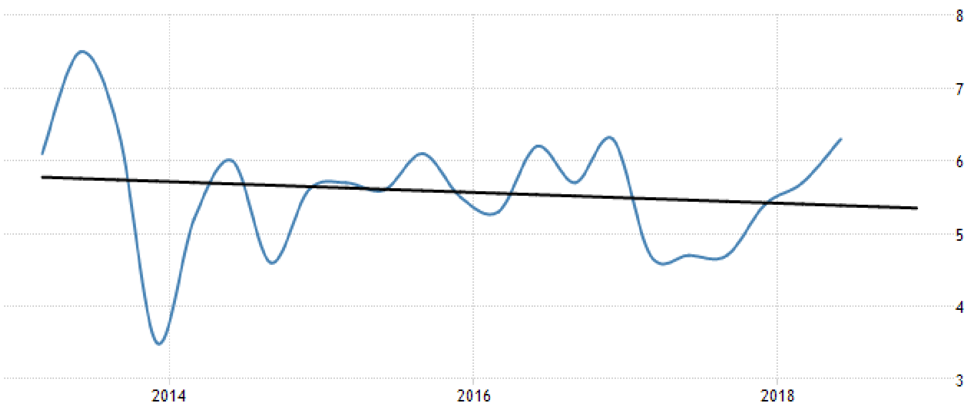
The VAR tests, however, do not show any causality of PCE_{ken} on GDP_{ken}. Shen & Lee (2006) argue that a reverse causality is more probable, because economic growth creates a fertile ground for better allocation of resources and better monitoring of capital, and because the economy is growing, there is a decreased amount of information asymmetry. As a consequence, banks would tend to extend credit more easily. These findings are consistent with those of Peia & Roszbach (2013), who find that whilst SMC can be the source of economic development, the reverse causality is more likely to occur with banking measures.

Figure 14: Gross non-performing loans to total gross loans ratio in Kenya

Source: (Financial Sector Regulators Forum, 2018)

The graph illustrates that the increase in the non-performing loans is an indication of poor performing assets, as a result of a declining economy. As the NPLs increase, banks cut back on their lending. Figure 15 below illustrates Kenyan GDP growth, which starts declining sharply in Q3 2013. The effect on credit lags by 12 months, as see in the NPLs (Figure 9), which goes to show that the case of a reverse causality, as put forward by other researchers (Peia & Roszbach, 2013; Shen & Lee, 2006), is more probable.

Figure 15: Kenya GDP annual growth rate

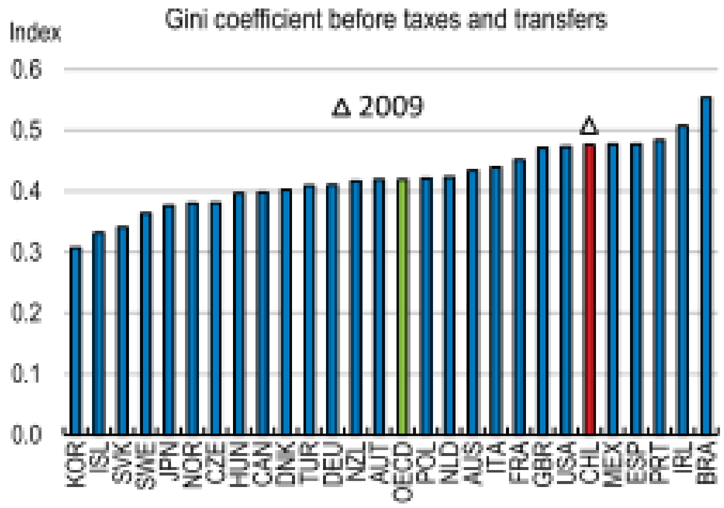


Retrieved from URL: https://tradingeconomics.com/kenya/gdp-growth-annual

6.6. Hypotheses 3b and 4b (PCE_{chi})

The results from the linear regression show that the model is statistically significant at a 95% confidence level and that the two independent variables are individually statistically significant. The PCE_{chi} coefficient is relatively large and has a very strong and positive correlation of 0.90, which is statistically significant. PCE_{chi} explains 82% of the variation in GDP_{chi}. A high coefficient and a very strong correlation could signal very active participation or the dominance of a single dominant economic factor. From Section 6.3., evidence has been presented to the effect that copper is a single and dominant resource export for Chile contributing 10% to its GDP and comprising 50% of all exports (EMIS, 2017). This effectively means that, credit can be advanced to firms and households, but because PCEchi is largely dependent on copper as a resource, on a few benefit and as a result, there is poor redistribution of wealth. Distribution is commonly measured by the Gini coefficient (Greenwood, Guner, Kocharkov, & Santos, 2014), which gauges economic inequality within a set population. Figure 11 illustrates the poor distribution of wealth in Chile, suggesting that even though there is an apparently high correlation between PCEchi and GDPchi, there is no causal relationship because there is no mass participation in the credit growth but instead, only a few benefit.

Figure 16: Inequality as measured by the Gini coefficient in Chile



Source: (OECD, 2018)

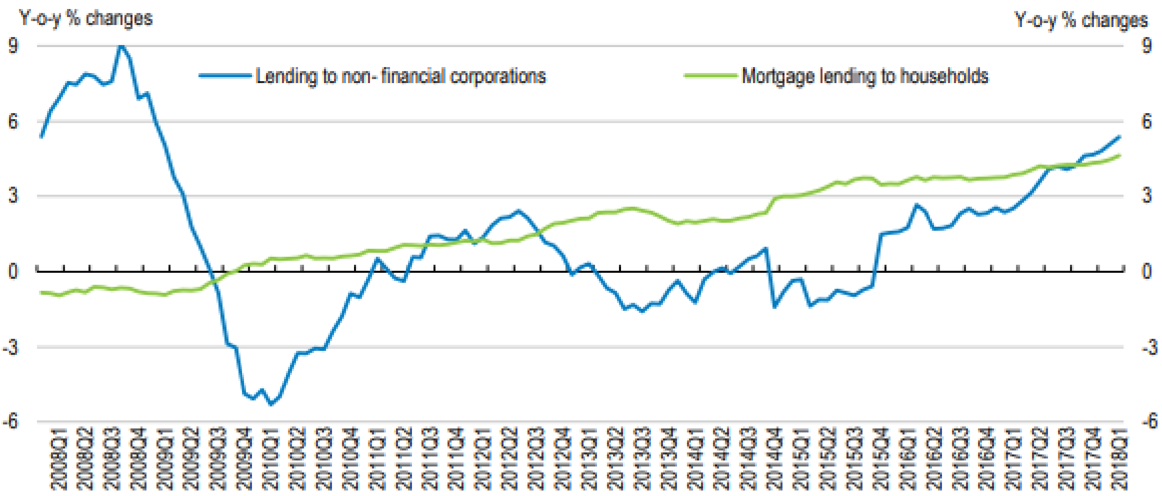
The results for PCE_{chi} causality on GDP_{chi} are statistically insignificant, indicating that increased bank participation in the economy cannot be the cause of any economic growth.

6.7. Hypotheses 3c and 4c (PCE_{deu})

The results from the linear regression show that the model is statistically significant at a 95% confidence level. Whilst SMC_{deu} is statistically significant, PCE_{deu} is not significant. This means that it is not a significant contributor to GDP_{deu}. The correlation, however, points to a statistically significant relationship between PCE_{deu} and GDP_{deu}: PCE_{deu} explains 39% of the variation in GDP_{deu}.

Causality tests show a statistically insignificant causality of PCE_{deu} on GDP_{deu} and instead show a reverse negative causality of GDP_{deu} on PCE_{deu}. This means that as GDP_{deu} increases, less and less bank measures of PCE_{deu} are required, as they may start to impede on economic growth. The reverse negative relationship is consistent with the theory of the inverted-U hypothesis (Cecchetti & Kharroubi, 2012; Samargandi et al., 2015), suggesting that increased financial deepening could start to impede economic growth. At the threshold of optimal finance-driven growth, the demand-following growth should respond and become more dominant (Alexiou & Vogiazas, 2018).

Figure 17: Growth of lending to non-financial corporation and mortgage to households



Source: OECD Germany, 2018

Whilst there is evidence indicating negative causality, it may not only be attributed to the inverted-U hypothesis; the graph above illustrates the negative shock that the 2008 financial crisis had on credit growth in Germany, and how it has been recovering.

CHAPTER 7. Conclusion

This research sought to understand the role that financial development has had on economic growth. If there is, indeed, a relationship, the study attempted to answer whether the relationship was causal or not. This would be determined and tested in two different ways:

- What particular financial measure is effective?
- Does the level of economic development matter?

Economic growth is at the top of many economic agendas worldwide in an attempt to fight unemployment and poor productivity. An important question in this context takes the following form: Is financial development a key driver to economic growth? This is a pertinent question that this study sought to examine. Economies are different in various ways, including but not limited to demographics, geography, resources, and skills; but this study focused on the level of development as defined by the IMF broad-based index for financial development.

7.1. Findings

This study undertook to contribute to the continuing study of financial development as a way to spur economic growth. This was done through exploring and investigating six objectives:

1. Determine whether financial development (market-based institutions) in low-income countries have any relationship with economic output, and whether this relationship is causal in nature. This is defined in hypotheses 1a and 2a.

2. Determine whether financial development (market-based institutions) in middle-income countries have any relationship with economic output, and whether this relationship is causal in nature. This is defined in hypotheses 1b and 2b.

3. Determine whether financial development (market-based institutions) in high-income countries, have any relationship with economic output, and whether this relationship is causal in nature. This is defined in hypotheses 1c and 2c.

4. Determine whether financial development (bank-based institutions) in low-income countries, have any relationship with economic output, and whether this relationship is causal in nature. This is defined in hypotheses 3a and 4a.

5. Determine whether financial development (bank-based institutions) in middle-income countries have any relationship with economic output, and whether this relationship is causal in nature. This is defined in hypotheses 3b and 4b.

6. Determine whether financial development (bank-based institutions) in high-income countries have any relationship with economic output, and whether this relationship is causal in nature. This is defined in hypotheses 3c and 4c.

7.1.1. Findings of hypotheses 1a and 2a

There is both a statistically significant correlation between SMCken and GDPken, and positive causality between SMCken on GDPken. The tests used were linear regression in determining the correlation, and the VAR test in determining causality.

These findings are consistent with Law & Singh (2014) in that growth is most likely to come from financial markets as opposed to banks, which tend to fund more consumption expenditure which is generally short term in nature. One also needs to take into account that Kenya has one of Africa's most developed securities market and that the country is a part of the leading pack in terms of innovation. This would suggest that there is some innovation-based growth that tends to be supported by financial markets and results in sustained economic growth (Browner & Ventura, 2016). Kenya is on the right path to economic prosperity and it is important for the country to continuously encourage the use and development of the securities market.

The objective is achieved and supported by research findings because the SMCken is relatively week in terms of the correlation to GDPken albeit positive and significant. What is more applicable to Kenya is the fact that its economy is moving towards an innovation-based arrangement, where SMC is likely to play a larger role.

7.1.2. Findings of hypotheses 1b and 2b

There is both a statistically significant correlation between SMCchi and GDPchi, and a positive causal relation between SMCchi on GDPchi. The tests used were linear regression in determining the correlation and the VAR test in determining causality.

The coefficients in the multiple regression are a lot larger relative to Kenya, hence implying a stronger correlation to GDP. This is consistent with the U-hypothesis (Cecchetti & Kharroubi, 2012; Law & Singh, 2014; Samargandi et al., 2015), showing that continued financial development starts to impact the economy more holistically. As far as Chile is concerned, there is evidence that suggests that the demand for financial services is driven by the abundant copper deposits, which is a theory that would be supported by the demand-leading hypothesis (Liu, 2003). The VAR test does not support this claim on Chile, however, and only shows a one-way direction, or just simply a supply-leading hypothesis.

The objective is achieved and supported by the research findings, as the SMCchi relationship with GDPchi strengthens signalling more participation in the financial markets as the economy develops and grows.

7.1.3. Findings of hypotheses 1c and 2c

There is both a statistically significant correlation between SMCdeu and GDPdeu, and a positive one-way causal relationship between SMCdeu on GDPdeu. The tests used were linear regression in determining the correlation and the VAR test in determining causality.

The results are consistent with the underlying theory that more developed countries tend to be innovation-driven economies and that support for innovation is more likely to come from the securities markets than from banking institutions (Henderson et al., 2013). Germany has a relatively high R&D expenditure (as seen in figure 13), which allows companies and start-ups alike to be supported in their initial price offering when they go to market. Banking institutions cannot provide this particular support.

The objective is achieved and supported by the research findings, as the causal relationship between SMCdeu and GDPdeu is positive and statistically significant.

7.1.4. Findings of hypotheses 3a and 4a

Whilst there is a statistically significant correlation between PCEken and GDPken, the VAR tests could not prove causality. These findings tend to be contrary to what the existing literature suggests, which is that, for low-income countries, growth is more likely to stem from banking institutions (Berkes et al., 2012). The high correlation of the two variables is due to a consumption pattern whereby higher GDP growth means high income and hence a higher propensity to spend. This spending translates to credit extended. There is no reverse causality to support this claim either, and we can conclude that PCEken does not have a causal relationship with GDP.

The objective is therefore not achieved as the research findings are not consistent with the inverted-U hypothesis (Law & Singh, 2014).

7.1.5. Findings of hypotheses 3b and 4b

Whilst there is a statistically significant high correlation between PCEchi and GDPchi, there is no causal relationship. This is because there is a poor income distribution, as measured by the Gini coefficient, and thus the credit extended does not reach a majority of the population. Similarly (Law & Singh, 2014) suggests that as economies develop, they use lesser of banking institutions and use more of securities market because they become more innovation-based.

One cannot conclude whether PCEchi is less effective because of the inverted-U hypothesis (Berkes et al., 2012) or whether there is poor credit reach in the economy of Chile. On the basis of the research limitations, however, we conclude that the objective is achieved, showing less PCE influence on the economy as it develops.

7.1.5. Findings of hypotheses 3c and 4c

There is a positive and statistically significant correlation between PCEdeu and GDPdeu but the coefficient is much less than that of PCEchi. Showing that PCE starts playing a less important or contributory role to GDP with more developed countries. PCEdeu does not have a causal relationship with GDPdeu either. The results also show a reverse and negative causality of GDPdeu on PCEdeu. This is supported by Hsu et al., (2014) who show that credit or bank-based financial systems tend to impede innovation and hence growth.

The objective has been achieved because there is evidence of slowing growth with excessive lending or PCE. We conclude that there is evidence of the inverted U-hypothesis.

7.1.6. Summary on principal findings

Private credit is positively correlated to the GDP growth of the country and, because it is short-term in nature, private credit is a function of GDP growth. The greater the growth, the more that banks will extend credit to firms and households. The short-term nature of PCE means that it is consumption-based and therefore does not have a causal effect on the growth of an economy.

The financial markets are a lot more efficient in allocating capital to business for growth. For this growth to be effective, businesses need to be innovation-driven because, fundamentally, financial markets fund innovation.

PCE has little impact, if any, on economic growth but the financial markets have a contributory role in the economic growth of a country.

7.2. Implications for management

South Africa has fallen from an overall GCI rank of 50 in 2011 to 61 in 2017 out of a 137 countries. Similarly its ranking in financial market development (i.e., the eighth pillar in the GCI), has dropped from 4th to 44th in the same time period (de Kock et al., 2017), with the full table being available in Appendix 9.11. The question that one would have to ask is: How has South Africa not grown to the level of its peers, which rank in the top ten of the financial market development pillar?

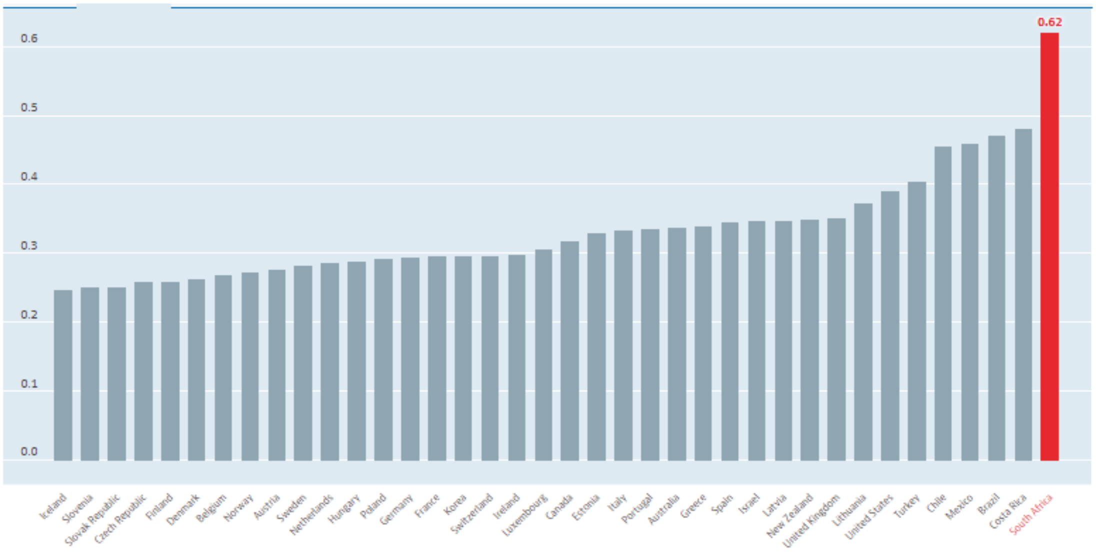
The research has highlighted two main points that will assist companies in the South African context to grow the economy.

1. South Africa is similar to Chile in the sense that it is an economy that is resource-dependent. Whilst the banks may seem to be participating in the economy, they are only servicing a few. The credit extended by the banks is therefore a function of the performance of the resource sector. When the resource sector performs, banks extend credit but not to the majority of the population. This is also evident from the graph below, which shows that South Africa is the most unequal society in the world, with a Gini coefficient of 0.62. It is therefore inconceivable to claim that credit extension will reach the majority of the population and create mass participation in bank credit. Effectively, this means that South Africa grows and leaves a majority of the population behind. The banking institutions therefore

have no real impact on the growth of South Africa but are merely a function of growth.

South African companies need to diversify out of resources and consider other sectors including technology and services. This will allow new sectors to form, which must be inclusive so that bank participation penetrates even the currently unbanked.

Figure 18: Income inequality measured by the Gini coefficient for chose countries

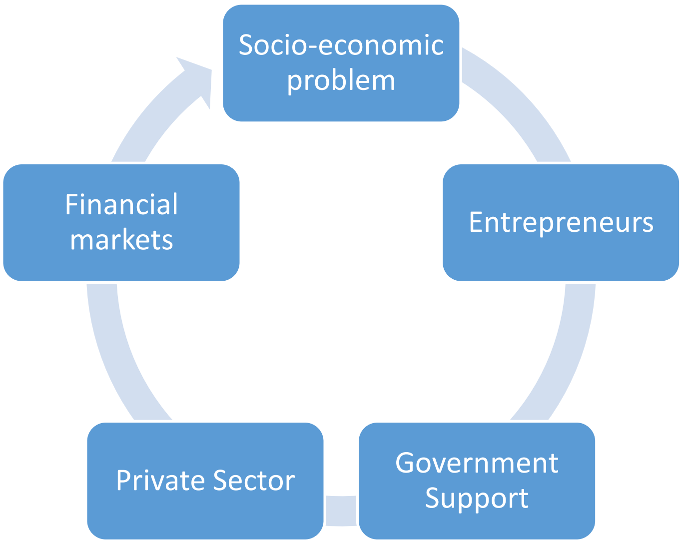


Source: https://data.oecd.org/inequality/income-inequality.htm

2. Financial markets have the greatest financial impact on the economy as shown in the results for Kenya, Chile, and Germany. Financial markets, however, are most effective in an innovation-based economy. South Africa is currently ranked 58th in the Global Innovation Index and below the median of the world average (Dutta, Lanvin, & Wunsch-Vincent, 2018). In order for the financial markets to be effective, the policies and institutions that govern new business must put more effort in supporting innovation-driven entrepreneurs and create a friendly ecosystem for them. Whilst 83% of new listings were in South Africa for 2017, only a small percentage was aimed at the innovation industry. Most of the listings were in consumer services (Steinhoff Africa Retail Ltd) and financials (African Rainbow Capital Investments Ltd and Long4Life Ltd) (PWC, 2017).

7.3. Model for economic growth

Figure 19: Model identified through the research



Source: Own research

The research has shown that whilst financial development has occurred, economic growth has not been inclusive in such a way that there would be mass participation in the economy. In Kenya, the financial markets are mostly foreign investors, while in Chile, less than 20% of the mining investors are local. This means that whilst financial markets can be potentially used to grow the economy, they tend to be no inclusive. The existing literature also suggests that financial markets are innovation-based and can therefore tackle economics challenges if properly incentivized (Rioja & Valev, 2014).

Figure 19 illustrates that for financial markets to effectively impact the economic growth in a sustainable and inclusive manner in South Africa, the entrepreneur must be incentivized and must receive support from government. Each country faces unique socio-economic challenges and yet the current ecosystem of foreign-based investors in the financial markets does not create an incentive to solve such challenges but are instead rather exploitative in nature.

7.4. Limitations

The research has various limitations, which include:

- Survivorship bias in both the SMC and PCE variables, since they do not show failed companies (SMC) or non-performing loans (PCE). Thus, with increasing Initial Public Offerings (IPOs) or a general increase in a bank's loan book, both

SMC and PCE can show an increase while there are failing businesses. This may be material information for the determination of economic growth.

- Stock markets in many countries can be centred on the country's key resource, e.g. agriculture in Kenya and copper mining in Chile, which may reflect growth in a specific sector as opposed to widespread growth. This can be misleading to policy-makers.
- There exists structural heterogeneity amongst economies, meaning that a singular policy may not necessary work across economies despite them being at a similar level of economic development.
- The VAR model is theoretical because it uses prior information, which further presents difficulties in choosing the appropriate lag length which it is highly sensitive to.
- The model is only valid for the range of data under consideration, 1966 – 2015 which also had missing data.
- Whilst the VAR model may give an indication of direction, it is still difficult to confirm causality.
- The data failed numerous pre-quality tests, which could result in false conclusions made.
- Financial development categories was based on the IMF broad-based index for financial development and on the GCI eighth pillar of competitiveness. These two indices have certain biases in their computation which would inevitable cause this current study to carry similar biases.

7.5. Future research recommendations

In consideration of the research limitations and the results from this study, we propose the following areas of research:

- In light of the very small sample size for the market-based measure, it would be well for future studies to examine more than one low-income country because low-income countries tend to have a small sample size for stock market data.

- Whilst securities markets have shown to be more effective in the countries specified, other countries in Africa may not have a vibrant and active stock exchange. In most countries in Africa, the debt capital markets are a lot more active and liquid as compared to the stock market. Research would have to extend to the debt capital markets to test whether they could potentially drive the economy.

7.6. Conclusion

This study has contributed to the body of knowledge on financial development as a driver for economic growth. This study will help policy-makers realize that economic growth through the financial markets must be a programme of intentional investing and that it cannot just be left to local or foreign investors. Entrepreneurs must be incentivized and supported by governments with the intention of promoting inclusivity through a wider market participation, which will then drive sustainable growth. Entrepreneurs that are not incentivized and supported will not invest to eradicate poverty but will rather invest for the purpose of self-enrichment, which is not sustainable for the wider economy.

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CHAPTER 9. Appendices

9.1. Data sources

Metric	Description	Period	Variable type	Source	Download URL
GDP_{ken}	Gross domestic product foe Kenya	Annual	Dependent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
GDP_{chi}	Gross domestic product foe Kenya	Annual	Dependent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
GDP_{deu}	Gross domestic product foe Kenya	Annual	Dependent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
PCE_{ken}	Private credit extension for Kenya	Annual	Independent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
PCE_{chi}	Private credit extension for Chile	Annual	Independent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
PCE_{deu}	Private credit extension for Germany	Annual	Independent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
SMC_{ken}	Stock market capitalization for Kenya	Annual	Independent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
SMC_{chi}	Stock market capitalization for Chile	Annual	Independent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators
SMC_{deu}	Stock market capitalization for Germany	Annual	Independent	World Bank	http://databank.worldbank.org/data/reports.aspx?source=world-development-indicators

Source: Own research

9.2. Preliminary descriptive statistics table

Statistics

	N	Minimum	Maximum	Mean	Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
GDPchl	50	3746.8154	14660.505	7726.4105	3565.6606	12713936.179	.555	.337	-1.151	.662
PCEchi	50	2.7500000	106.88000	49.753400	31.142179	969.835	-.014	.337	-.955	.662
SMCchi	27	27.410000	137.16000	88.722222	24.064715	579.111	-.622	.448	1.210	.872
GDPdeu	46	19625.918	45260.081	32842.320	7715.9267	59535525.357	-.071	.350	-1.216	.688
PCEdeu	50	59.510000	116.33000	86.909199	15.533721	241.297	.159	.337	-.869	.662
SMCdeu	41	7.5900000	64.240000	29.155853	16.580839	274.924	.367	.369	-1.066	.724
GDPken	50	599.24782	1133.4585	862.47501	114.63440	13141.047	-.335	.337	1.194	.662
PCEken	50	12.230000	34.810000	21.891199	5.5163222	30.430	.330	.337	-.334	.662
SMCken	24	5.1500000	39.960000	19.942500	11.110410	123.441	.168	.472	-1.367	.918

Source: Own research

9.3. Model quality tests

9.3.1. The Akaike Information Criterion

9.3.1.1. Kenya (hypothesis 2a and 4a)

VAR system, maximum lag order 4

Table 40: AIC

lags	loglik	p(LR)	AIC	BIC	HQC
1	-176.94484		18.894484	19.491924*	19.011111
2	-164.05166	0.00221	18.505166	19.550685	18.709262
3	-155.81834	0.05775	18.581834	20.075432	18.873400
4	-142.04412	0.00113	18.104412*	20.046090	18.483448*

Source: Own research

9.3.1.2. Chile (hypothesis 2b and 4b)

VAR system, maximum lag order 4

Table 41: AIC

lags	loglik	p(LR)	AIC	BIC	HQC
1	-287.52107		26.045310	26.637742	26.194305
2	-272.01833	0.00030	25.479855	26.516610*	25.740596
3	-263.59907	0.05131	25.530354	27.011433	25.902841
4	-248.50751	0.00041	25.000653*	26.926056	25.484886*

Source: Own research

9.3.1.3 Germany (hypothesis 2c and 4c)

VAR system, maximum lag order 4

Table 42: AIC

lags	loglik	p(LR)	AIC	BIC	HQC
1	-494.75532		27.392180	27.914640	27.576371
2	-477.01625	0.00005	26.919797	27.834102*	27.242133
3	-468.91981	0.06296	26.968638	28.274788	27.429117
4	-453.73888	0.00038	26.634534*	28.332528	27.233156*

Source: Own research

9.4. Unit Root Test

9.4.1. Germany

9.4.1.1. GDPdeu

Table 43: GDPdeu ADF test

```
Augmented Dickey-Fuller test for GDPdeu
testing down from 1 lags, criterion AIC
sample size 45
unit-root null hypothesis: a = 1

  with constant and trend
  including one lag of (1-L)GDPdeu
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.63912
  test statistic: tau_ct(1) = -4.45871
  asymptotic p-value 0.001706
  1st-order autocorrelation coeff. for e: 0.081
```

Source: Own research

Since p-value (0.0017) < p-α(0.05), we reject the null hypothesis and conclude that the data is stationary.

9.4.1.2. PCEdeu

Table 44: PCEdeu ADF test

```
Augmented Dickey-Fuller test for PCEdeu
testing down from 1 lags, criterion AIC
sample size 48
unit-root null hypothesis: a = 1

  with constant and trend
  including one lag of (1-L)PCEdeu
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): 0.00719262
  test statistic: tau_ct(1) = 0.18059
  asymptotic p-value 0.9979
  1st-order autocorrelation coeff. for e: 0.030
```

Source: Own research

Since p-value (0.18059) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.4.1.3. SMCdeu

Table 45: SMCdeu ADF test

```
Augmented Dickey-Fuller test for SMCdeu
testing down from 1 lags, criterion AIC
sample size 39
unit-root null hypothesis: a = 1

  with constant and trend
  including one lag of (1-L)SMCdeu
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.31266
  test statistic: tau_ct(1) = -3.32242
  asymptotic p-value 0.06257
  1st-order autocorrelation coeff. for e: 0.104
```

Source: Own research

Since p-value (0.06257) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.4.2. Chile

9.4.2.1. GDPchi

Table 46: GDPchi ADF test

Augmented Dickey-Fuller test for GDPchi
testing down from 1 lags, criterion AIC
sample size 48
unit-root null hypothesis: a = 1
with constant and trend
including one lag of (1-L)GDPchi
model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
estimated value of (a - 1): -0.0675629
test statistic: tau_ct(1) = -1.96173
asymptotic p-value 0.6216
1st-order autocorrelation coeff. for e: 0.026

Source: Own research

Since p-value (0.6216) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.4.2.2. PCEchi

Table 47: PCEchi ADF test

Augmented Dickey-Fuller test for PCEchi
testing down from 1 lags, criterion AIC
sample size 48
unit-root null hypothesis: a = 1
with constant and trend
including one lag of (1-L)PCEchi
model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
estimated value of (a - 1): -0.168814
test statistic: tau_ct(1) = -3.44693
asymptotic p-value 0.04534
1st-order autocorrelation coeff. for e: -0.007

Source: Own research

Since p-value (0.04534) < p-α(0.05), we reject the null hypothesis and conclude that the data is stationary.

9.4.2.3. SMCchi

Table 48: SMCchi ADF test

```
Augmented Dickey-Fuller test for SMCchi
testing down from 1 lags, criterion AIC
sample size 25
unit-root null hypothesis: a = 1
  with constant and trend
  including one lag of (1-L)SMCchi
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.53506
  test statistic: tau_ct(1) = -2.94477
  asymptotic p-value 0.1483
  1st-order autocorrelation coeff. for e: 0.090
```

Source: Own research

Since p-value (0.1483) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.4.3. Kenya

9.4.3.1. GDPken

Table 49: GDPken ADF test

```
Augmented Dickey-Fuller test for GDPken
testing down from 1 lags, criterion AIC
sample size 48
unit-root null hypothesis: a = 1
  with constant and trend
  including one lag of (1-L)GDPken
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.140164
  test statistic: tau_ct(1) = -2.16596
  asymptotic p-value 0.5082
  1st-order autocorrelation coeff. for e: 0.038
```

Source: Own research

Since p-value (0.5082) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.4.3.2. PCEken

Table 50: PCEchi ADF test

```
Augmented Dickey-Fuller test for PCEken
testing down from 1 lags, criterion AIC
sample size 49
unit-root null hypothesis: a = 1

  with constant and trend
  including 0 lags of (1-L)PCEken
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + e
  estimated value of (a - 1): -0.171637
  test statistic: tau_ct(1) = -2.04356
  p-value 0.5634
  1st-order autocorrelation coeff. for e: 0.029
```

Source: Own research

Since p-value (0.5634) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.4.3.3. SMCken

Table 51: SMCchi ADF test

```
Augmented Dickey-Fuller test for SMCken
testing down from 1 lags, criterion AIC
sample size 24
unit-root null hypothesis: a = 1

  with constant and trend
  including one lag of (1-L)SMCken
  model: (1-L)y = b0 + b1*t + (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.429497
  test statistic: tau_ct(1) = -3.05607
  asymptotic p-value 0.1171
  1st-order autocorrelation coeff. for e: 0.055
```

Source: Own research

Since p-value (0.1171) > p-α(0.05), we fail to reject the null hypothesis and conclude that the data is non-stationary.

9.5. Cointegration

9.5.1. Kenya

Table 52: AEG test

```
Augmented Dickey-Fuller test for uhat
including one lag of (1-L)uhat
sample size 24
unit-root null hypothesis: a = 1

  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.200139
  test statistic: tau_c(3) = -1.53326
  asymptotic p-value 0.8891
  1st-order autocorrelation coeff. for e: 0.009
```

Source: Own research

Since p-value (0.8891) > p-α(0.05), we fail to reject the null hypothesis and conclude no cointegration

9.5.2. Chile

Table 53: AEG test

```
Augmented Dickey-Fuller test for uhat
including one lag of (1-L)uhat
sample size 25
unit-root null hypothesis: a = 1

  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.47874
  test statistic: tau_c(3) = -3.64558
  asymptotic p-value 0.06346
  1st-order autocorrelation coeff. for e: 0.012
```

Source: Own research

Since p-value (0.06346) > p-α(0.05), we fail to reject the null hypothesis and conclude no cointegration

9.5.3. Germany

Table 54: AEG test

```
Augmented Dickey-Fuller test for uhat
including one lag of (1-L)uhat
sample size 39
unit-root null hypothesis: a = 1

  model: (1-L)y = (a-1)*y(-1) + ... + e
  estimated value of (a - 1): -0.282802
  test statistic: tau_c(3) = -3.16294
  asymptotic p-value 0.1809
  1st-order autocorrelation coeff. for e: 0.072
```

Source: Own research

Since p-value (1809) > p-α(0.05), we fail to reject the null hypothesis and conclude no cointegration

9.6. Data transformation

Table 55: DW test on transformed log equation

Model Summary[b]

					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson

				the Estimate						
1	.979[a]	.959	.956	.05568	.959	283.017	2	24	.000	.670

a. Predictors: (Constant), SMCchiLOG, PCEchiLOG

b. Dependent Variable: GDPchiLOG

Source: Own research

Rejection region

If $d < d_L$	reject $H_0: \rho = 0$
If $d > d_U$	do not reject $H_0: \rho = 0$
If $d_L < d < d_U$	test in inconclusive

For n = 27, k = 1 and for $\alpha = 0.05$,

d_L = 1.316 and $d_U = 1.469$

Reject H_0 and conclude that there exists autocorrelation

9.7. Vector auto regressive models

9.7.1. Kenya (hypothesis 2a and 4a)

VAR system, lag order 4
Equation 1: GDPken

Table 56: GDPken VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	53.9291	161.169	0.3346	0.7477	
GDPken_1	0.741765	0.375264	1.977	0.0886	*
GDPken_2	−0.224745	0.509698	−0.4409	0.6726	
GDPken_3	−0.184167	0.574924	−0.3203	0.7581	
GDPken_4	0.421171	0.394068	1.069	0.3206	
PCEken_1	8.18698	4.78180	1.712	0.1306	
PCEken_2	0.770736	5.53082	0.1394	0.8931	
PCEken_3	−10.0097	7.12270	−1.405	0.2027	
PCEken_4	6.58030	5.66271	1.162	0.2833	
SMCken_1	2.93156	1.33503	2.196	0.0641	*
SMCken_2	−3.55409	2.04362	−1.739	0.1256	
SMCken_3	3.82316	1.86355	2.052	0.0793	*
SMCken_4	−1.48229	1.15653	−1.282	0.2408	

Mean dependent var	896.6095	S.D. dependent var	64.20546
Sum squared resid	2375.047	S.E. of regression	18.41989

R-squared	0.969677	Adjusted R-squared	0.917694
F(12, 7)	18.65388	P-value(F)	0.000368
rho	−0.429456	Durbin-Watson	2.736673

Source: Own research

Equation 2: PCEken

Table 57: PCEken VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−2.11244	9.45259	−0.2235	0.8295	
GDPken_1	−0.000377231	0.0220093	−0.01714	0.9868	
GDPken_2	0.00493473	0.0298939	0.1651	0.8736	
GDPken_3	−0.00790091	0.0337194	−0.2343	0.8214	
GDPken_4	0.00894030	0.0231122	0.3868	0.7104	
PCEken_1	0.150920	0.280454	0.5381	0.6072	
PCEken_2	0.494406	0.324384	1.524	0.1713	
PCEken_3	0.387520	0.417748	0.9276	0.3845	
PCEken_4	−0.213944	0.332120	−0.6442	0.5400	
SMCken_1	−0.0316239	0.0782996	−0.4039	0.6984	
SMCken_2	0.125668	0.119859	1.048	0.3293	
SMCken_3	−0.141161	0.109298	−1.292	0.2375	
SMCken_4	0.201355	0.0678309	2.968	0.0209	**

Mean dependent var	25.30950	S.D. dependent var	4.195868
Sum squared resid	8.169823	S.E. of regression	1.080332
R-squared	0.975576	Adjusted R-squared	0.933707
F(12, 7)	23.30036	P-value(F)	0.000177
rho	−0.478378	Durbin-Watson	2.923017

Source: Own research

Equation 3: SMCken

Table 58: SMCken VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−67.9494	41.6415	−1.632	0.1467	
GDPken_1	−0.0409761	0.0969579	−0.4226	0.6853	
GDPken_2	0.149296	0.131692	1.134	0.2943	
GDPken_3	−0.0949972	0.148544	−0.6395	0.5428	
GDPken_4	0.0628551	0.101816	0.6173	0.5566	
PCEken_1	−1.58034	1.23548	−1.279	0.2416	
PCEken_2	2.26397	1.42901	1.584	0.1571	
PCEken_3	−2.66250	1.84031	−1.447	0.1912	
PCEken_4	2.60695	1.46309	1.782	0.1180	
SMCken_1	1.48537	0.344934	4.306	0.0035	***
SMCken_2	−1.55474	0.528015	−2.945	0.0216	**
SMCken_3	1.04743	0.481491	2.175	0.0661	*
SMCken_4	−0.512713	0.298816	−1.716	0.1299	

Mean dependent var	22.81650	S.D. dependent var	9.859804
Sum squared resid	158.5493	S.E. of regression	4.759191

R-squared	0.914163	Adjusted R-squared	0.767014
F(12, 7)	6.212497	P-value(F)	0.011240
rho	−0.228929	Durbin-Watson	2.432483

Source: Own research

9.7.2. **Chile (hypothesis 2b and 4b)**

VAR system, lag order 4

Equation 1: GDPchi

Table 59: GDPchi VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	210.400	228.709	0.9199	0.3793	
GDPchi_1	0.409273	0.283098	1.446	0.1789	
GDPchi_2	0.290113	0.305235	0.9505	0.3643	
GDPchi_3	0.378730	0.343646	1.102	0.2962	
GDPchi_4	−0.271776	0.207045	−1.313	0.2186	
PCEchi_1	−13.1691	18.6923	−0.7045	0.4972	
PCEchi_2	5.72276	33.1479	0.1726	0.8664	
PCEchi_3	41.7948	32.9257	1.269	0.2331	
PCEchi_4	−10.5799	27.8278	−0.3802	0.7118	
SMCchi_1	12.8592	4.53559	2.835	0.0177	**
SMCchi_2	−1.57091	5.78030	−0.2718	0.7913	
SMCchi_3	5.21928	4.71145	1.108	0.2939	
SMCchi_4	−9.75566	4.34927	−2.243	0.0488	**

Mean dependent var	11169.96		S.D. dependent var	2135.494
Sum squared resid	213705.0		S.E. of regression	146.1865
R-squared	0.997870		Adjusted R-squared	0.995314
F(12, 10)	390.3887		P-value(F)	1.10e-11
rho	−0.283807		Durbin-Watson	2.546315

Source: Own research

Equation 2: PCEchi

Table 60: PCEchi VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−3.96662	3.55602	−1.115	0.2907	
GDPchi_1	0.00697778	0.00440167	1.585	0.1440	
GDPchi_2	−0.00821381	0.00474586	−1.731	0.1142	
GDPchi_3	0.00424700	0.00534308	0.7949	0.4452	
GDPchi_4	−0.00116253	0.00321919	−0.3611	0.7255	
PCEchi_1	1.61619	0.290632	5.561	0.0002	***
PCEchi_2	−1.07502	0.515391	−2.086	0.0636	*
PCEchi_3	0.156390	0.511937	0.3055	0.7663	
PCEchi_4	0.0677806	0.432672	0.1567	0.8786	
SMCchi_1	−0.00531858	0.0705203	−0.07542	0.9414	
SMCchi_2	0.0392753	0.0898733	0.4370	0.6714	

SMCchi_3	−0.0826401	0.0732547	−1.128	0.2856	
SMCchi_4	0.0631440	0.0676234	0.9338	0.3724	

Mean dependent var	76.15000		S.D. dependent var	17.36452
Sum squared resid	51.66256		S.E. of regression	2.272940
R-squared	0.992212		Adjusted R-squared	0.982866
F(12, 10)	106.1685		P-value(F)	6.99e-09
rho	−0.099793		Durbin-Watson	2.157002

Source: Own research

Equation 3: SMCchi

Table 61: SMCchi VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	17.9986	11.7606	1.530	0.1569	
GDPchi_1	−0.00220679	0.0145574	−0.1516	0.8825	
GDPchi_2	0.0328226	0.0156957	2.091	0.0630	*
GDPchi_3	−0.00532769	0.0176709	−0.3015	0.7692	
GDPchi_4	−0.00744156	0.0106466	−0.6990	0.5005	
PCEchi_1	−0.686489	0.961191	−0.7142	0.4914	
PCEchi_2	2.62945	1.70452	1.543	0.1539	
PCEchi_3	−1.34594	1.69310	−0.7950	0.4451	
PCEchi_4	−2.00519	1.43095	−1.401	0.1914	
SMCchi_1	0.678869	0.233228	2.911	0.0155	**
SMCchi_2	−0.345919	0.297233	−1.164	0.2715	
SMCchi_3	0.164411	0.242271	0.6786	0.5128	
SMCchi_4	−0.847804	0.223647	−3.791	0.0035	***

Mean dependent var	95.49435		S.D. dependent var	17.15985
Sum squared resid	565.0781		S.E. of regression	7.517168
R-squared	0.912771		Adjusted R-squared	0.808097
F(12, 10)	8.720113		P-value(F)	0.000874
rho	−0.041375		Durbin-Watson	1.938523

Source: Own research

9.7.3. **Germany (hypothesis 2c and 4c)**

Equation 1: GDPdeu

Table 62: GDPdeu VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	3272.89	2348.14	1.394	0.1761	
GDPdeu_1	0.777463	0.216660	3.588	0.0015	***
GDPdeu_2	−0.234862	0.285251	−0.8234	0.4184	
GDPdeu_3	0.0104752	0.279260	0.03751	0.9704	
GDPdeu_4	0.408366	0.210479	1.940	0.0642	*
PCEdeu_1	−76.2337	48.3749	−1.576	0.1281	
PCEdeu_2	32.0733	71.4381	0.4490	0.6575	
PCEdeu_3	21.8449	71.3542	0.3061	0.7621	
PCEdeu_4	10.8702	48.0946	0.2260	0.8231	

SMCdeu_1	90.6768	28.1614	3.220	0.0037	***
SMCdeu_2	−139.453	41.1197	−3.391	0.0024	***
SMCdeu_3	124.188	46.7909	2.654	0.0139	**
SMCdeu_4	−67.6439	32.2045	−2.100	0.0464	**

Mean dependent var	35461.07		S.D. dependent var	6145.089
Sum squared resid	9255331		S.E. of regression	620.9982
R-squared	0.993192		Adjusted R-squared	0.989788
F(12, 24)	291.7629		P-value(F)	5.95e-23
rho	0.132943		Durbin-Watson	1.689953

Source: Own research

Equation 2: PCEdeu

Table 63: PCEdeu VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−15.5735	8.88432	−1.753	0.0924	*
GDPdeu_1	0.000398377	0.000819747	0.4860	0.6314	
GDPdeu_2	0.00115478	0.00107926	1.070	0.2953	
GDPdeu_3	0.00104825	0.00105660	0.9921	0.3310	
GDPdeu_4	−0.00232246	0.000796362	−2.916	0.0076	***
PCEdeu_1	1.27610	0.183030	6.972	<0.0001	***
PCEdeu_2	−0.191283	0.270291	−0.7077	0.4860	
PCEdeu_3	0.567517	0.269973	2.102	0.0462	**
PCEdeu_4	−0.548890	0.181969	−3.016	0.0060	***
SMCdeu_1	−0.113532	0.106550	−1.066	0.2972	
SMCdeu_2	0.180054	0.155579	1.157	0.2585	
SMCdeu_3	−0.517427	0.177036	−2.923	0.0075	***
SMCdeu_4	0.241921	0.121848	1.985	0.0586	*

Mean dependent var	93.21865		S.D. dependent var	11.52030
Sum squared resid	132.4933		S.E. of regression	2.349586
R-squared	0.972269		Adjusted R-squared	0.958404
F(12, 24)	70.12168		P-value(F)	1.12e-15
rho	0.021410		Durbin-Watson	1.944065

Source: Own research

Equation 3: SMCdeu

Table 64: SMCdeu VAR

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	−37.3254	16.4744	−2.266	0.0328	**
GDPdeu_1	−0.00165708	0.00152008	−1.090	0.2865	
GDPdeu_2	0.00258834	0.00200131	1.293	0.2082	
GDPdeu_3	−0.00203170	0.00195928	−1.037	0.3101	
GDPdeu_4	0.00207725	0.00147671	1.407	0.1723	
PCEdeu_1	0.200391	0.339397	0.5904	0.5604	
PCEdeu_2	−0.480115	0.501207	−0.9579	0.3477	
PCEdeu_3	0.817820	0.500619	1.634	0.1154	
PCEdeu_4	−0.281364	0.337430	−0.8338	0.4126	
SMCdeu_1	1.39089	0.197579	7.040	<0.0001	***

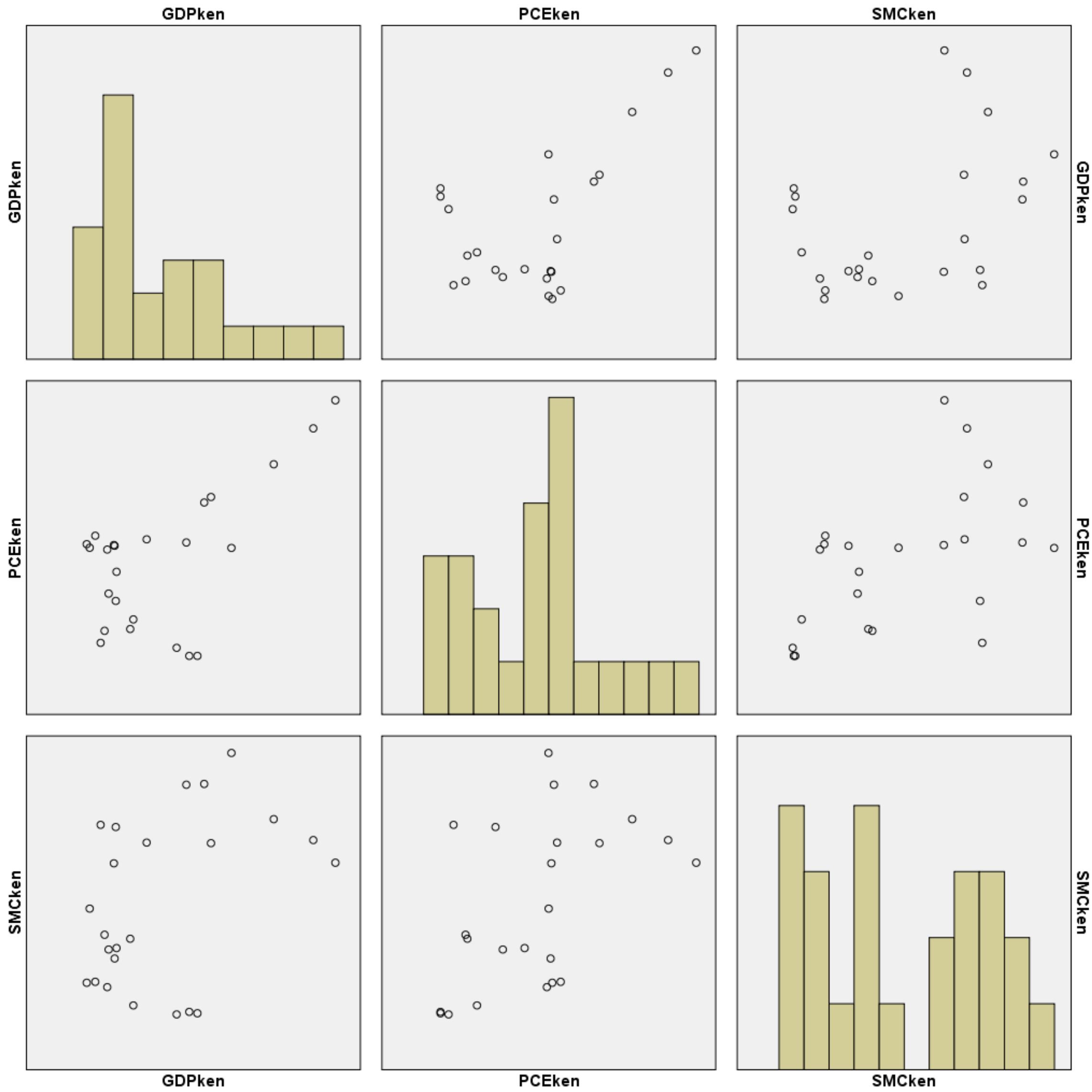
SMCdeu_2	−1.21953	0.288494	−4.227	0.0003	***
SMCdeu_3	0.726191	0.328283	2.212	0.0367	**
SMCdeu_4	−0.491984	0.225946	−2.177	0.0395	**

Mean dependent var	31.18459		S.D. dependent var	16.18964
Sum squared resid	455.5816		S.E. of regression	4.356899
R-squared	0.951718		Adjusted R-squared	0.927576
F(12, 24)	39.42290		P-value(F)	7.91e-13
rho	0.114310		Durbin-Watson	1.700362

Source: Own research

9.8. Linearity scatter plots for Kenya

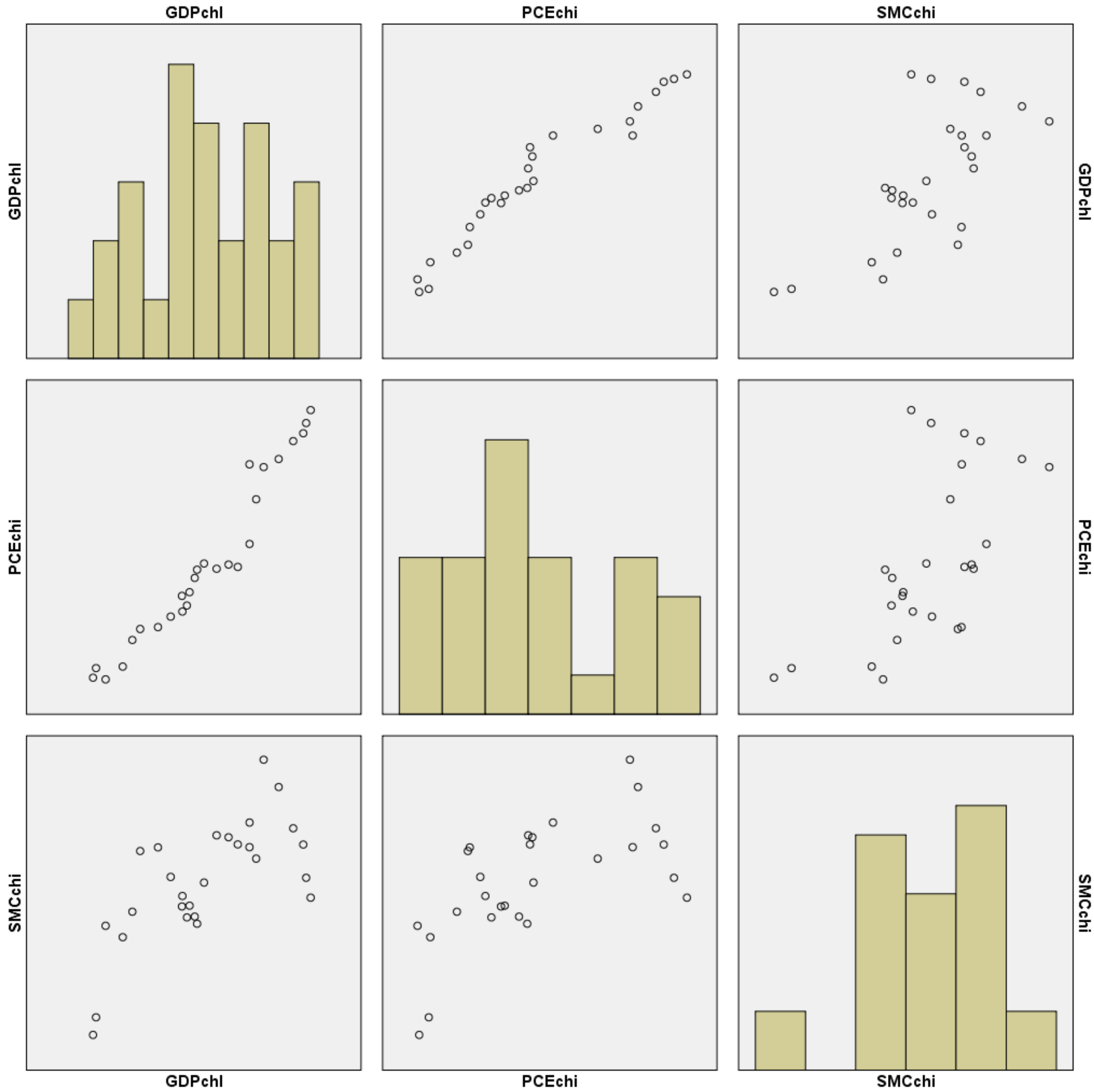
Figure 20: Linearity scatter plots for Kenya



Source: Own research

9.9. Linearity scatter plots for Chile

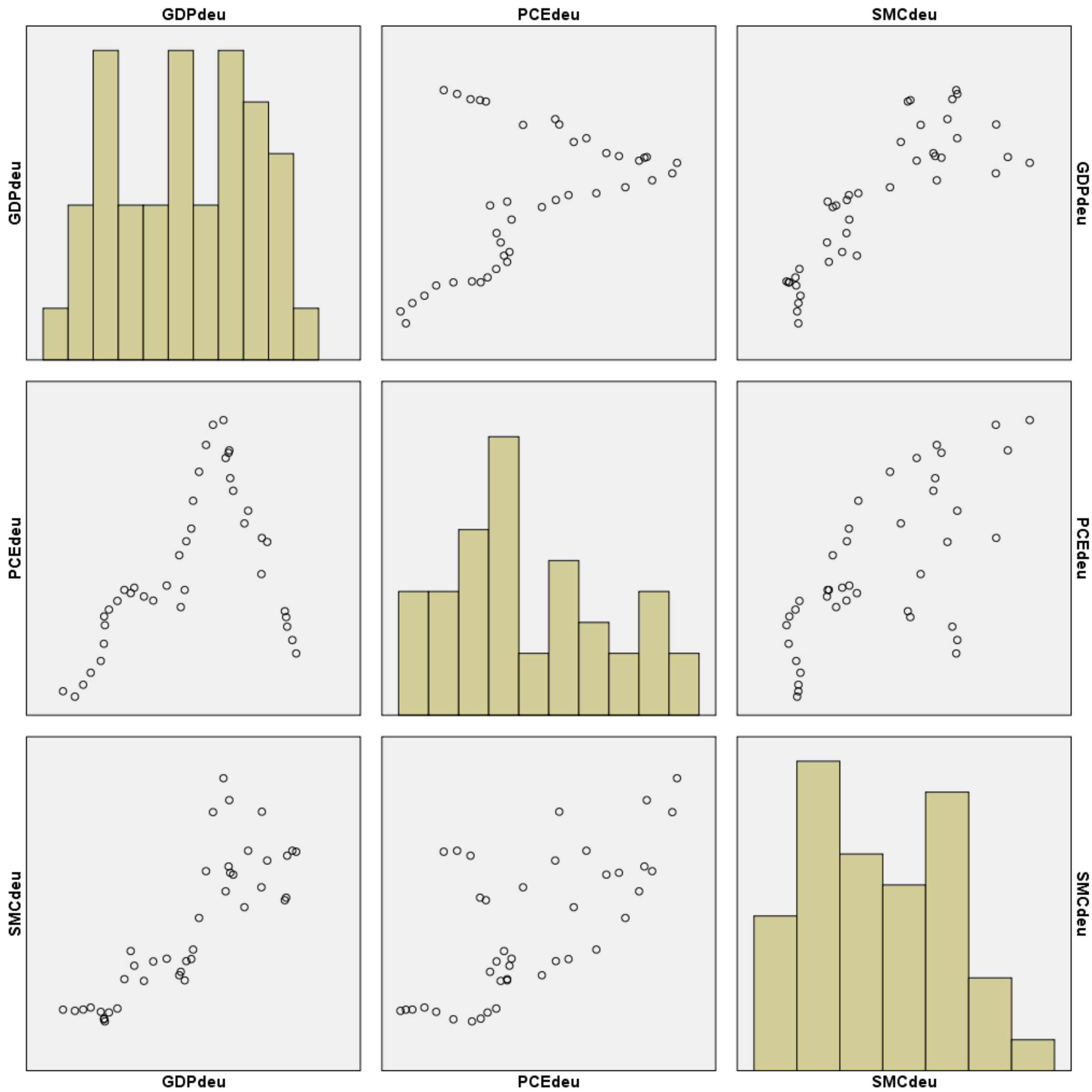
Figure 21: Linearity scatter plots for Chile



Source: Own research

9.10. Linearity scatter plots for Germany

Figure 22: Linearity scatter plots for Germany



Source: Own research

9.11. GCI rankings from 2011-2017

Figure 23: GCI rankings from 2011 - 2017

	South Africa's Performance on WEF GCI 2011-2017/18						
	2011	2012	2013	2014	2015	2016	2017/18
Overall	50	52/144	53/148	56/144	49/140	47/138	61/137
Institutions	46	43	41	36	38	40	76 ↓
Infrastructure	62	63	66	60	68	64	61 ↑
Macro-Economic Environment	55	69	95	89	85	79	82 ↓
Health & Primary Education	131	132	135	132	126	123	121 ↑
Higher Education & Training	73	84	89	86	83	77	85 ↓
Goods & Market Efficiency	32	32	28	32	38	28	54 ↓
Labour Market Efficiency	95	113	116	113	107	97	93 ↑
Financial Market Development	4	3	3	7	12	11	44 ↓
Technological Readiness	76	62	62	66	50	49	54 ↓
Market Size	25	25	25	25	29	30	30 →
Business Sophistication	38	38	35	31	33	30	37 ↓
Innovation	41	42	39	43	38	35	39 ↓

Source: (de Kock et al., 2017)

9.12. Consistency matrix

Hypotheses	Description	Literature review	Data collection tool	Analysis method
1. correlation of SMC and GDP	To determine whether there is correlation between GDP and stock market capitalization for the three categories of low, medium and high level of financial development.	(Arestis et al., 2016; Levine, Loayza, & Beck, 2000; Levine & Zervos, 2008)	Secondary data sources from www.worldbank.org and www.imf.org	• Pearson correlation analysis • Simple linear regression • Multiple linear regression
2. causality between SMC and GDP	To determine whether there is causality between GDP and stock market capitalization for the three categories of low, medium and high level of financial development.	(Arestis et al., 2016; Levine et al., 2000; Levine & Zervos, 2008)	Secondary data sources from www.worldbank.org and www.imf.org	• Granger causality test • Vector auto regression test
3. correlation between PCE and GDP	To determine whether there is correlation between GDP and private credit extension for the three categories of low, medium and high level of financial development.	(Durusu-Ciftci et al., 2017; Romer, 2015; Samargandi et al., 2015)	Secondary data sources from www.worldbank.org and www.imf.org	• Pearson correlation • Simple linear regression • Multiple linear regression

Hypotheses	Description	Literature review	Data collection tool	Analysis method
4. causality between PCE and GDP	To determine whether there is causality between GDP and private credit extension for the three categories of low, medium and high level of financial development.	(Aghion, Howitt, & Mayer-Foulkes, 2005; Law & Singh, 2014; Peia & Roszbach, 2013)	Secondary data sources from www.worldbank.org and www.imf.org	• Granger causality test • Vector auto regression test