**UNIVERSITY OF GHANA**

**COLLEGE OF HUMANITIES**

# DO CREDIT INFORMATION SHARING SCHEMES MATTER TO BANK PROFITABLITY? EVIDENCE FROM AFRICA

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**DEPARTMENT OF FINANCE**

**JULY 2016**

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# DO CREDIT INFORMATION SHARING SCHEMES MATTER TO BANK PROFITABLITY? EVIDENCE FROM AFRICA

**BY**

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**A THESIS SUBMITTED TO THE UNIVERSITY OF GHANA BUSINESS SCHOOL IN PARTIAL FULFILMENT OF THE AWARD OF DEGREE OF MASTER OF PHILOSOPHY IN FINANCE**

**DEPARTMENT OF FINANCE**

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# DECLARATION

I do hereby declare that this work is the result of my own research and has not been presented by anyone for any academic award in this or any other university. All references used in the work have been fully acknowledged.

I bear sole responsibility for any shortcomings.

…… ……

NORMAN ADU BAMFO DATE

(10508910)

# CERTIFICATION

I hereby certify that this thesis was supervised in accordance with procedures laid down by the University of Ghana.

…….. ……..

PROF A Q.Q. ABOAGYE DATE

(PRINCIPAL SUPERVISOR)

…….. ……..

DR. PATRICK ASUMING DATE

(SUPERVISOR)

# DEDICATION

This work is dedicated to my father, Mr. Frank Adu Bamfo and my siblings, Abigail Adu Bamfo and Lawrence Adu Bamfo for their encouragement throughout the period of my studies.

# ACKNOWLEDGEMENT

I thank the Almighty God for all His wisdom, strength, and mercies throughout the period of this study.

I would like to express my sincere appreciation to my supervisors Prof A.Q.Q Aboagye and Dr. Patrick Asuming for their guidance and constructive criticisms which shaped the quality of this study.

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| | | |
|---|---|---|
| BLUE | - | Best Linear Unbiased Estimator |
| CID | - | Depth of Credit Information sharing |
| CPI | - | Consumer Price Index |
| CTIR | - | Cost To Income Ratio |
| ETA | - | Equity to Total Assets |
| GDP | - | Gross Domestic Product |
| GDPG | - | Gross Domestic Product Growth |
| GMM | - | Generalized method of moments |
| HHI | - | Herfindhal-Hirschman Index |
| IBCA | - | International Bank Credit Analysis |
| LTA | - | Loan to Total Assets |
| NIM | - | Net Interest Margin |
| NPL | - | Non-performing loans |
| OLS | - | Ordinary Least Square |
| PCB | - | Private Credit Bureau |
| PCR | - | Public Credit Registry |
| PERI | - | Political Economy Research Institute |
| ROA | - | Return on Assets |
| ROAA | - | Return on Average Assets |
| ROE | - | Return on Equity |
| SW | - | Shapiro – Wilk |
| US | - | United States |
| VAR | - | Vector Autoregression |
| VIF | - | Variance Inflation Factor |
| WDI | - | World Development Indicators |

# ABSTRACT

The study investigates the profitability of banks within 41 African countries from the period 2004 to 2013 at different levels of credit information sharing using the depth of credit information index to measure the extent of credit information sharing (i.e. the rules/laws and practice affecting the coverage, scope and accessibility of credit information available either through private bureaus/public registries) in Africa. The extent of credit information sharing is also disaggregated into Private Credit Bureau coverage and Public Credit Registry Coverage to capture the relative impacts of the two distinct forms of credit information sharing schemes on bank profitability.

A Fixed Effects regression model was employed on unbalanced panel data from the Bank Scope Database.The results indicate that banks are profitable when there is voluntary credit information sharing through the Private Credit Bureaus, whiles compulsory credit information exchanges through Public credit Registries used as government antitrust policy mechanism which fosters competition has an insignificant impact on the profitability of banks in Africa. The study further shows that the extent of credit information sharing in Africa does not significantly support bank profitability as the depth of credit information sharing is low in Africa. Nevertheless, credit information sharing through Private Credit Bureaus significantly matters in enhancing bank profitability whiles other bank specific factors such as Capital Adequacy, Credit Risk and Management/Operational efficiency also significantly explains the variations in the profitability of banks in Africa.

These results are suggestive of the fact that banks can improve their profitability by credit information exchanges through private credit bureaus to alleviate related information asymmetric problems, whereas controlling for the level of equity, non-performing loans and enhancing managerial/operational efficiency can further improve profitability. Thus, government measures and policies must provide the enabling financial environment that will accelerate growth and improve bank profitability.

# CHAPTER ONE
# INTRODUCTION

## 1.1 Research Background

Financial intermediation through the banking system plays pivotal roles in the growth and development of most economies (Schumpeter, 1911). The various functions banks perform, such as mobilization of savings, evaluation of projects, resource allocation, management of risk, monitoring of managers and facilitation of transactions (Levine, 1997) cannot be overemphasized. Hitherto, research (see Fosu, 2014; Francis, 2013; Flamini, 2009; Nissanke & Aryeetey, 2006) on bank profitabilty in the Africa Region has been a concern, attracting considerable and further attention among scholars, academic and practitioners (Fujii, Managi & Matousek, 2014).

The significance of financial institutions and their stability is due to their ability to mitigate problems of economies of scale in information gathering and the allocation of risk under asymmetric information (Agenor, 2000). One of the enormous risks financial institutions and particularly banks face in their operating activities pertains to credit (Greenidge & Tiffany, 2010), making profits volatile (Beck & Levine, 2004; Karbo & Adamu, 2009). This is because, the likelihood of default for any particular borrower surges as the amount borrowed increases (Stiglitz 1970, 1972; Freimer & Gordon, 1965).

The seminal work of Stiglitz and Weiss (1981), on the study of credit rationing in market with imperfect information, also confirms that lack of accurate and complete borrower's information

in taking lending decisions leads to adverse selection and moral hazard as a result of information asymmetry. They further posit that taking lending decisions by focusing on interest and physical collateral is inadequate, since that can discourage safe borrowers and might include risky borrowers which can decrease banks' profits.

Banks more often than not are unaware of the past behaviors, features and intentions of their loan customers. This causes banks to make their lending decisions based on average attributes rather than individual characteristics of their borrowers (Kerage & Jagongo, 2014) translating into low profits. It has been argued in extant literature that one of the ways banks can reduce such risk is through credit information sharing (Gaitho, 2013). Information sharing helps to predict the future behavior from past behavior (Matthews & Thompson, 2009), reduces adverse selection (Pagano & Jappelli, 1993), facilitate the assessment of credit requests to reduce the risks of bad debts and helps overcome the problems of moral hazard (Padilla and Pagano, 2000) by raising the efforts of borrowers to repay loans and thereby improving profits.

Martinez and Singh (2014), explained that Credit Information Sharing Schemes are mechanisms that can help lenders and borrowers overcome asymmetric information problems, because the scheme allows lenders to share with other lenders information about their clients, either through a privately held Credit bureau or Publicly Regulated Credit Registry. Such schemes disseminate knowledge of payment history, credit worthiness and total debt exposure, thus bridging the information divide between lenders and borrowers. However, a well-developed and effective credit information sharing scheme is what matters (Jappelli & Pagano, 2000), as they offer timely, credible and objective information on borrowers, and allow financial institutions to

reduce loan processing time and cost by 20% or more, and reduce or cut default rate by 40 to 80% improving profitability and overall performance.

The perceived importance of credit information sharing schemes to banks in developing economies, especially Africa cannot be overemphasized. Despite, the main source of income for most banks being the traditional activity of lending, banks in developing economies are reluctant to grant more credits which may cause decreases in their profitability. This is partly because unlike their developed counterparts, these economies are characterized by weak legal and judicial systems (Brown, Jappelli, & Pagano, 2009), inadequate transparency in corporate reporting and weak creditor rights which may increase the tendency of defaults on the loan demand side of their balance sheets/ statement of financial position.

As at 2012, 8 countries had established credit bureaus in Sub-Saharan Africa while 7 countries have credit bureaus established in Middle East and North Africa and only two countries (Nigeria and Ghana) in the West Africa Sub-Region have credit bureau at that time (World Bank, Doing Business Indicators, 2012). Middle East and North African countries have recently seen a growing interest in credit reporting, and Tunisia, Egypt and Morocco successfully reformed their credit information system in 2015. However, between 2002 and 2007, important legal changes were made to enable private credit bureau operations in Ghana, Uganda, Tanzania and Zambia, and at least three private credit bureaus were established in Nigeria. Several countries, including Mozambique, Angola, Madagascar, and Mauritius have initiatives to develop credit information sharing schemes since its impact on the performance of financial institutions (banks) cannot be underestimated.

The literature on credit information sharing in Africa has emphasized its impact on the efficiency of credit markets (Padilla & Pagano, 2000, 1997; Pagano & Japelli, 1993) without much emphasis on its overall effect on profitability. This study therefore seeks to examine the impact of credit information sharing schemes on the profitability of banks in Africa.

**1.2 Problem Statement**

The financial infrastructure in the African region is nascent (Mwangi, 2005), as far as Credit Information Sharing Schemes are concern. The inadequate credit information coupled with bank inefficiencies and macroeconomic downturns makes the African banking market underdeveloped compared to other developing countries (Honohan & Beck, 2007; Mylenko, 2007). On the average, the allocation of credit to the private sector by banks in Africa lags behind (Mylenko, 2007). Beck, Demirguc-Kunt, and Levine (2009), also reported that the region has the lowest credit penetration in the world with less than 20% of households having access to formal banking services. This shows inadequate collaterals, poor credit facilities and a weak financial infrastructure going a long way to adversely affect profitability within the banking system. This presupposes that banks therefore generate less profit as a result of low credit allocation or loans, which is however considered as the major activity of banks.

Nevertheless, the region is making strides in the development of credit information sharing schemes to capture reports that enables financial institution (banks) to shift from physical collateral to reputational collateral (both negative and positive information, containing details on all open and closed credit accounts, credit amounts, and repayment behavior), as countries within the region make attempts to widen credit history reports through expanding Public credit registry and Private credit bureau coverage (see figures 1.1 & 1.2). Credit registry/ bureau coverage

reports the number of individuals and firms listed in their database with information on their borrowing history within the past five years, plus the number of individuals and firms that have had no borrowing history in the past five years but for which a lender requested a credit report from the registry/ bureau. It is expressed as a percentage of the adult population (the population aged 15 and above in 2014 according to the World Bank's *World Development Indicators, 2015*). If no credit registry/ bureau exist the value is 0.0%

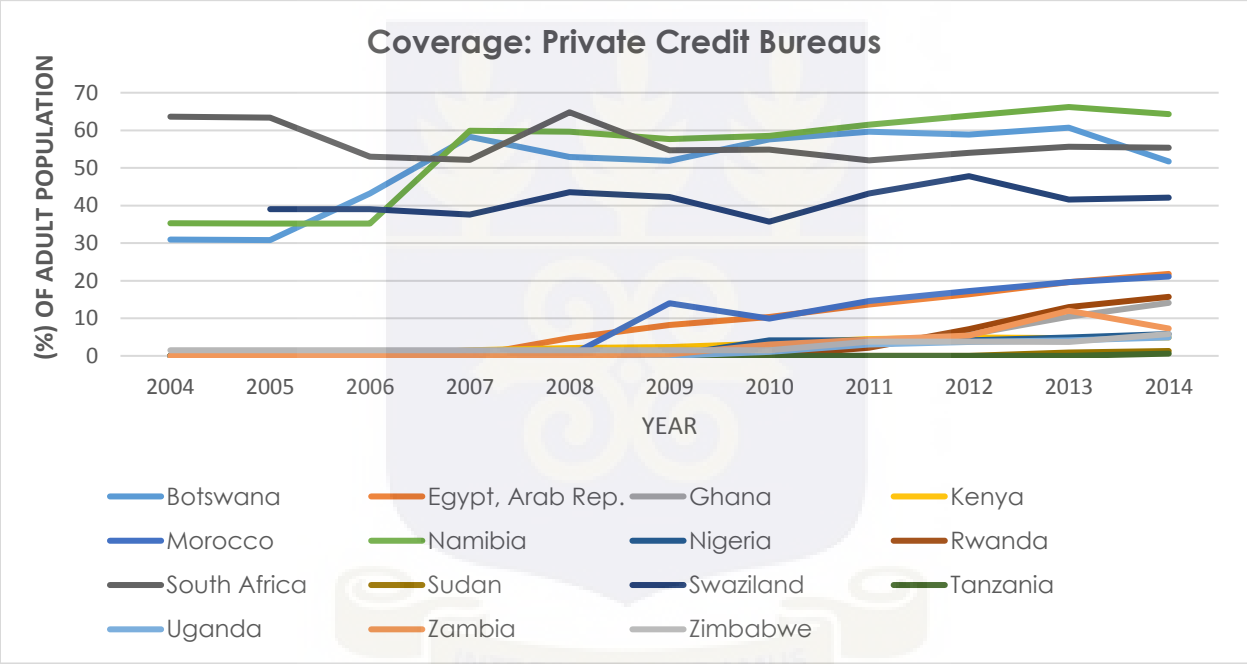


**Figure 1.1: Coverage: Private Credit Bureaus**
***Source: Plot from WDI Database (2004 – 2014)***

From Figure 1.1, fifteen (15) countries have private credit bureau coverage out of which four (4) countries namely: Namibia, Botswana, South Africa and Swaziland have high coverage ranging from 30% to 70%, while the remaining countries show about 20% and below. Country specific private bureau coverage seem to have high values relative to public registry coverage (compare with figure 1.2) though limited in scope (just 15 countries over the period).

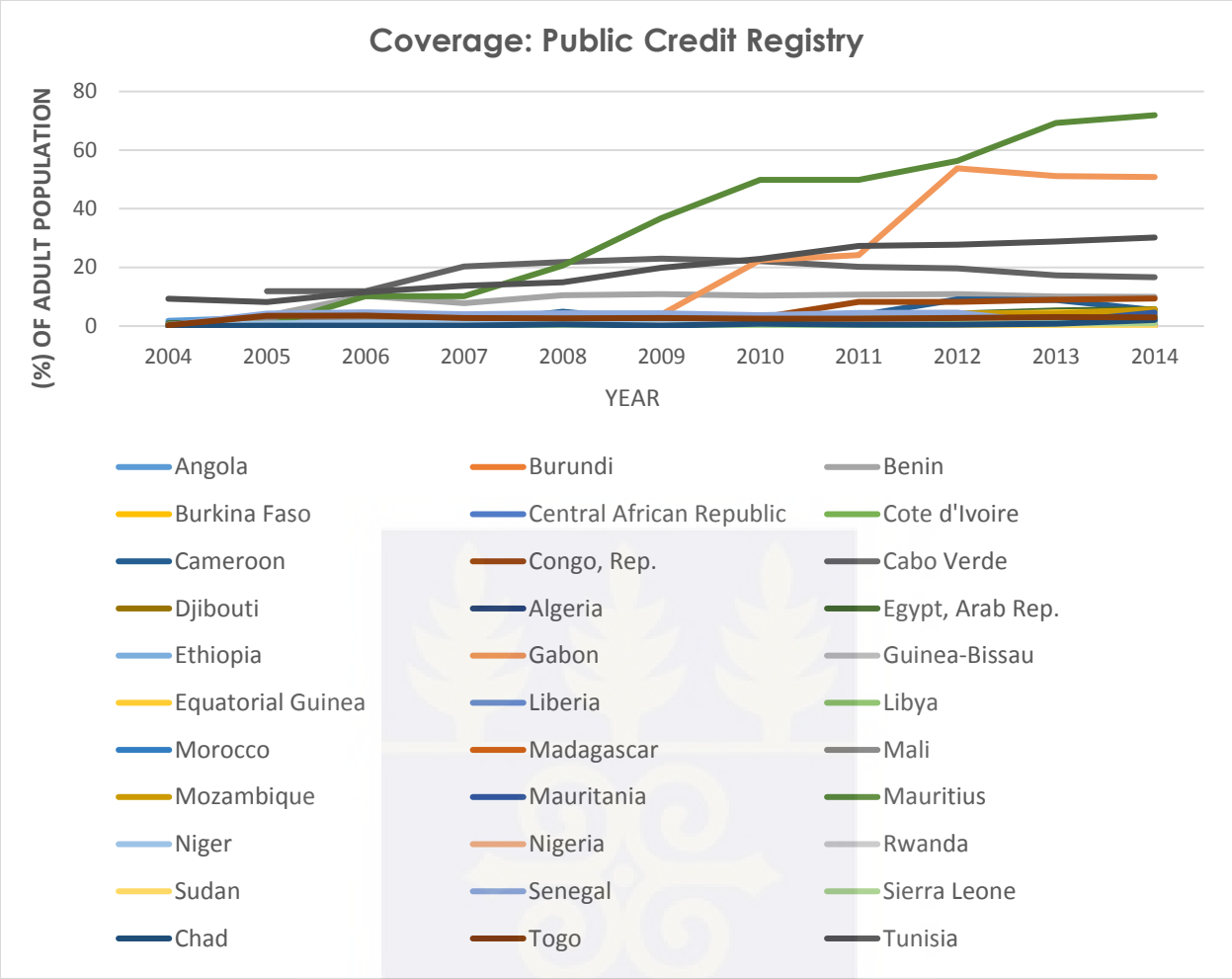


**Figure 2: Coverage: Public Credit Registry**
***Source: Plot from WDI Database (2004 – 2014)***

Figure 1.2 depicts that the Africa Region is predominantly driven by Public credit coverage in terms of credit information sharing schemes. It covers a wider scope (33 African countries) but shallow in coverage (relative to values of private bureau coverage). Only two countries (Mauritius and Gabon) consistently reports coverage reaching about 71% and 51% respectively by the end of 2014. The remaining (31 countries) lags behind with Tunisia reaching 30% by 2014 and the rest clustering below a 20% threshold.

A major challenge in developing credit history report by Public registries/Private bureaus in Africa is the small size of the credit markets, as credit bureaus rely on economies of scale to cover their large up-front investment through the sale of credit reports. Another important challenge could be related to the lack of national IDs, the absence of physical addresses, or variations in names. Hence, these irregularities and challenges within the credit information sharing system or framework tends to raise concerns about the depth (rules and practices affecting the coverage, scope and accessibility) of Credit Information Sharing Schemes in the Africa Region. This study seeks to provide an empirical evidence to unravel the potential impact of the depth of credit information sharing schemes on the performance (profitability) of the banking system in Africa, which cannot be determined a priori.

However, previous studies (Behr & Sonnekalb, 2012; Barron & Staten, 2003; Kallberg & Udell, 2003; Powell et al., 2004; Louto et al. 2007; Brown & Zehnder, 2007) suggest that information sharing (through Private Credit Bureaus) have disciplinary effect on borrowers financial behavior as a result of future denial of access to credit by other lenders. Also, through enhanced lenders knowledge on borrowers, it can reduce adverse selection, moral hazard problems and improve overall bank performance. Hence, banks can be more profitable because credit information shared through Public registry/Private bureaus discipline borrowers and allows banks predict clients more accurately to ignore less credit worthy clients. This enable banks to retrieve all loans and advances (principal plus interest) to increase return on their asset allocations.

To a large extent, this undoubtedly can be achieved given the accuracy/correctness of credit data, broad scope/coverage, good quality and accessibility of these credit information sharing schemes

(Jappeli & Pagano, 2000). Credit information sharing is therefore expected to facilitate lending decisions (Bennardo, Pagano, & Piccolo, 2010; Pagano & Jappelli, 1993), reduce loan default by increasing borrowers' incentive to repay (Padilla & Pagano, 1997, 2000), and increase competition which in turn leads to higher lending (Pagano & Jappelli, 1993). The benefits of information sharing are hypothesized to be particularly helpful in less consolidated or more competitive banking markets, where borrower credit information is dispersed (Marquez, 2002). Although recent empirical interest has been drawn to the potential benefits of credit information sharing on lending decisions, access to credit (Luoto, Mcintosh, & Wydick, 2007), credit risk and quality, bank concentration (Fosu, 2014), hitherto, considerable attention has not been given to the overall impact of Credit Information Sharing Schemes on the profitability of banks, especially the African banking system (see Berger et al., 2005).

Moreover, studies (e.g. Flamini, McDonald & Schumacher, 2009; Francis, 2013; Naceur, 2003 and among others) on the determinants or factors influencing profitability of banks in the Africa region are limited and scanty failing to capture information asymmetry effects which are absorbed through credit information schemes. This study examines the impact of credit information sharing schemes on the profitability of banks in the Africa region, and disaggregates credit information sharing through private bureaus and public registries whiles controlling for other bank specific, industry and macroeconomic factors that influence profitability of banks.

This is in response to previous suggestions proposed by different scholars that there is the need for more research and information on the performance of banks in Africa (Francis, 2013), and extensive studies on credit information sharing schemes within emerging regions like Africa (Jappelli & Pagano, 2000) to make informed policy decisions.

### 1.3 Research Objectives

This research principally examines the impact of credit information sharing schemes on the profitability of the banking system in Africa. To achieving this main objective, the specific objectives are;

1. To examine the impact of the depth (coverage, scope & accessibility) of credit information sharing schemes on banks' profitability in Africa.
2. To investigate the relative impacts of public credit registries versus private credit bureaus' coverage on banks' profitability in Africa.

### 1.4 Research Questions

To achieve these research objectives, the following questions are addressed.

1. Does the depth of credit information schemes in Africa have significant impact on banks' profitability?
2. Does public credit registry and private credit bureau coverage influence banks' profitability in Africa?

### 1.5 Significance of the Study

The study of the impact of credit information schemes on the profitability of the banking system in Africa has much significance. This study will contribute to the body of knowledge in the area of credit information sharing schemes and bank profitability, especially in the Africa Region. Providing empirical evidence; the extent of how the coverage, scope and accessibility of credit information available through either credit bureau or credit registry in Africa can alleviate information asymmetry effect to considerably harness the profitability of the banking system, and also other factors that influences profitability of banks in the Africa Region.

It is evidently noted that although the impact of credit information sharing is well researched (on credit risk/loan default, bank lending, firm access to finance & credit extensions, bank corruption, bank crisis, bank concentration) in Europe, United States and Asia, focus on bank profitability has been scanty and as well very little attention has been drawn towards the Africa Region. Hence this study will lead to more informed knowledge on Africa and its financial infrastructure on credit sharing.

The study will also serve as a guide that will inform policymakers, bank management and brokers of credit information systems to adopt desirable approach to improving their scope of operations to achieve optimum benefits.

For engrossed researchers in the areas of Credit Information Sharing and bank profitability, this study will serve as a guide for future researchable areas under these broad topics in the context of Africa and its regional blocs, countries and income level brackets across the globe.

### 1.6 Chapter Disposition

The study entails six chapters with sub-chapters. Chapter one encompasses the background of the area of study, problem statement, objective of the study, research hypothesis, significance of the study and its limitations as well as the chapter disposition.

Chapter two provides a review of the Depth (coverage, scope & accessibility) of Credit Information Sharing (using the Depth of Credit Information Index), and assessing the public

credit registry & private credit bureau coverage within the Africa Region. Providing a trend analysis in either case from the study period 2004 to 2013.

Chapter three captures the scholarly literature; both significant theoretical and empirical review, salient issues and profound opinion of several authors based on the study. This chapter provides a review on information asymmetry, credit information sharing, moral hazard, adverse selection, bank profitability theories and discusses relevant empirical studies on bank profitability.

Chapter four discusses the methodology employed by the study. This chapter highlights on the research design, population, sample and sampling technique, data collection, model specification, selection of variate and covariates as well as the method of analyses.

Chapter five focuses on the presentation and interpretations of the data collected for the study, and provide detail discussion and findings of results. The summary, conclusion and recommendations of the study is captured in Chapter six.

### 1.7 Chapter Conclusion

In a summary, this chapter sought to provide the motivation and set the tone that necessitated the study in Africa and point out the issue gap in extant literature that the study seeks to fill.

# CHAPTER TWO

# CREDIT INFORMATION SHARING IN AFRICA

## 2.1 Introduction

This chapter attempts to provide an overview of the depth, scope and coverage of credit information sharing in Africa from 2004 to 2014. The chapter provides graphs and tables to examine the trends of credit information sharing schemes and bank profitability in the Africa Region. This is to ensure a better understanding and support of the arguments presented in this study.

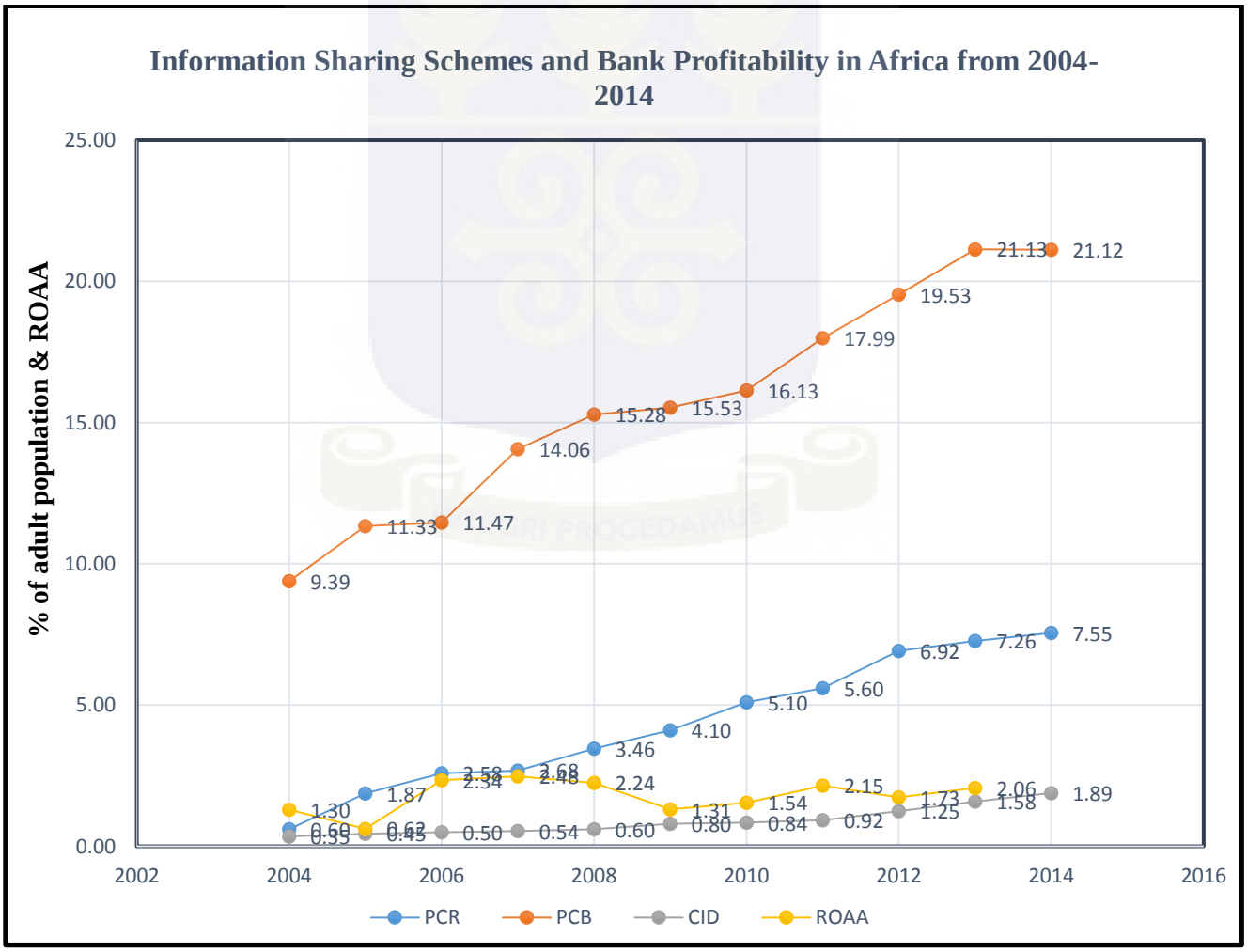


**Figure 2 : Trends in Information Sharing Scheme and Bank Profitability in Africa from 2004-2014 (Source: Plotted from World Development Indicators Database 2004 – 2014)**

**2.2 Credit Information Sharing Variables & bank Profitability in Africa**

Figure 2 above shows the trends in bank credit information sharing variables and profitability in Africa from 2004 to 2014. The credit information sharing variables includes private credit bureau coverage (PCB), Public Credit Registry coverage (PCR) and credit information depth index (CID), bank profitability includes ROAA. The study employs the averages of the variables to plot this figure.

The depth of Credit information sharing Index measures the rules and practices affecting the coverage, scope and accessibility of credit information sharing through either private or public bureaus. The index ranges from 0 to 8, with higher values indicating the availability of more credit information, from either a public registry or a private bureau, to facilitate lending decisions. Private Credit Bureau coverage measures and reports information on the borrowing history of individuals and firms as a percentage of adult population in a given country covered or captured in the database of private credit information sharing institutions, while Public Credit Registry coverage reports the credit history of individuals and firms as a percentage of adults population in a country covered or captured in the database of public credit information sharing institutions.

From the figure, private credit bureau coverage (red line) which measures the percentage of adult population covered by private credit information sharing institutions has shown a consistent increase in their coverage of adult population. An average percentage of private credit bureau coverage of 9.39% is recorded in 2004, 11.33% in 2005, 11.47% in 2006, 14.06% in 2007, 15.28% in 2008, 15.53% in 2009, 16.13% in 2010, 17.99% in 2011, 19.53% in 2012, 21.13% in 2013 and 21.12% in 2014. Although there is a persistent and steady increases in private credit

bureau coverage from year to year, there appears to be a marginal decrease from 21.13 in 2013 to 21.12 in 2014. The continuous increases in private credit bureau proves the strong presence of private credit bureaus in Africa.

Public credit registry coverage (blue line) which measures the percentage of adult population covered by public credit information sharing institutions has also illustrated a persistent increase in their coverage of adult population. An average percentage of Public Credit Registry coverage of 0.60% is recorded in 2004, 1.87% in 2005, 2.58% in 2006, 2.68% in 2007, 3.46% in 2008, 4.10% in 2009, 5.10% in 2010, 5.60% in 2011, 6.92% in 2012, 7.26% in 2013 and 7.55% in 2014. The figure show a consistent and persistent steady increase in Public Credit Registry coverage in Africa from 2004 to 2014. Although there is a constant and persistent increase in both private credit bureau coverage and Public Credit Registry coverage, private credit bureau coverage increases supersedes that of public credit registry in Africa. This indicates that the presence or coverage of private credit bureau is stronger in Africa

The Depth of credit information sharing Index (CID - grey line) measures the rules/laws and practices affecting the coverage, scope and accessibility of credit information sharing through credit information sharing institutions (either private credit bureaus or public credit registry).The chart above show an average credit information sharing index at 0.35 index in 2004, 0.45 in 2005, 0.50 in 2006, 0.54 in 2007, 0.60 in 2008, 0.80 in 2009, 0.84 in 2010, 0.92 in 2011, 1.25 in 2012, 1.58 in 2013 and 1.89 in 2014. The figure show constant and marginal increases in the rules affecting the coverage, scope and accessibility of the information shared in Africa from 2004 to 2014. Although the depth of credit information increases steadily, values of the credit information sharing index is very low. This indicates that although credit information sharing

institutions are operational in Africa, the rules/laws and practice in terms of operations affecting the coverage, scope and accessibility through the credit information sharing scheme is very low or weak.

ROAA (yellow line) which measures the profitability of banks also illustrates an unstable trend. An average bank profitability 1.30% is recorded in 2004, 0.62% in 2005, 2.34% in 2006, 2.48% in 2007, 2.24% in 2008, 1.31% in 2009, 1.54% in 2010, 2.15% in 2011, 1.73% in 2012 and 2.06% in 2013. The figure show an unstable pattern in Africa from 2004 to 2014. The pattern suggests a low profitability in African banks and unstable pattern.

**Table 1: Country Ranking of Private Credit Bureau Coverage**

| Country Name | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | COUNTRY AVERAGE | COUNTRY RANK |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Botswana | 30.9 | 30.8 | 43.2 | 58.3 | 52.9 | 51.9 | 57.6 | 59.6 | 58.9 | 60.7 | 51.7 | 50.6 | 3 |
| Egypt, Arab | 0 | 0 | 0 | 0 | 4.7 | 8.2 | 10.3 | 13.7 | 16.4 | 19.6 | 21.8 | 8.6 | 6 |
| Ghana | 0 | 0 | 0 | 0 | 0 | 0 | 2.1 | 3.3 | 5.7 | 10.4 | 14.1 | 3.2 | 8 |
| Kenya | 0.1 | 0.1 | 0.1 | 1.5 | 2.1 | 2.3 | 3.3 | 4.5 | 4.9 | 4.7 | 4.9 | 2.6 | 10 |
| Morocco | 0 | 0 | 0 | 0 | 0 | 14 | 9.9 | 14.6 | 17.2 | 19.6 | 21.1 | 8.8 | 5 |
| Namibia | 35.3 | 35.2 | 35.2 | 59.9 | 59.6 | 57.7 | 58.5 | 61.5 | 63.9 | 66.2 | 64.3 | 54.3 | 2 |
| Nigeria | 0 | 0 | 0 | 0 | 0 | 0 | 4.1 | 4.1 | 4.1 | 4.9 | 5.8 | 2.1 | 12 |
| Rwanda | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 2.2 | 7.1 | 13 | 15.7 | 3.5 | 7 |
| South Africa | 63.6 | 63.4 | 53 | 52.1 | 64.8 | 54.7 | 54.9 | 52 | 54 | 55.6 | 55.4 | 56.7 | 1 |
| Sudan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.9 | 1.3 | 0.2 | 14 |
| Swaziland | | 39 | 39 | 37.6 | 43.5 | 42.3 | 35.7 | 43.2 | 47.8 | 41.6 | 42.1 | 41.2 | 4 |
| Tanzania | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.6 | 0.1 | 15 |
| Uganda | 0 | 0 | 0 | 0 | 0 | 0 | 1.1 | 3 | 3.7 | 4.1 | 4.9 | 1.5 | 13 |
| Zambia | 0 | 0 | 0 | 0 | 0.1 | 0.4 | 3 | 4.3 | 5.4 | 12 | 7.3 | 3.0 | 9 |
| Zimbabwe | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 | 3.8 | 3.8 | 3.7 | 5.8 | 2.5 | 11 |
| **Overall Country Average** | | | | | | | | | | | | **15.9** | |

**Source: Computed from World Development Indicators Database**

### 2.3 Trend in Private Credit Bureau Coverage in Africa

Table 1 above shows the yearly private credit bureau coverage of countries that share credit information through private institutions in Africa. The yearly coverage of private credit bureau coverages are summarized by finding the average of private credit bureaus for each country and overall country average from 2004 to 2014.

From the database employed, 15 countries were identified to share credit information in Africa through private credit bureaus over the periods under study. South Africa, Namibia, Botswana, Swaziland and Morocco recorded the highest private credit bureau coverage recording an adult percentage coverage of 56.7%, 54.3%, 50.6%, 41.2% and 8.8% respectively. The table shows a strong presence of private credit bureau coverage in Southern Africa as the first four countries with the highest adult percentage coverage through private bureaus are located in Southern Africa. Again, the fifth country (Morocco) with the highest private credit bureau coverage is located in the Northern Africa and recorded an average 8.8% adult coverage through private credit bureau coverage. The difference in private credit bureaus coverage between the fourth and fifth place countries with highest private credit bureau coverage reechoes the strong presence of private credit bureaus in Southern Africa.

Again, aside the first four countries with the highest private credit bureau coverage (which are all Southern African countries), all the other eleven countries that share credit information through private credit bureaus recorded country averages below the overall country average. Interestingly, the table shows that the last three countries with the lowest private credit bureau coverage are Tanzania, Sudan and Uganda which recorded 0.1%, 0.2% and 1.5% respectively.

Overall the average coverage of private credit bureaus is low as it show a nearly 16% coverage of adult population coverage in Africa. Also, 11 out of 15 countries that share credit information through private credit bureaus recorded a private bureau coverage below the overall country average. This is an indication that most countries that share credit information through private credit bureaus have low private credit bureau coverage in Africa. At the country levels, private credit bureau coverage show a consistent and stable growth in private credit bureau coverage in Africa between 2004 and 2014.

Table 2**: Country Ranking of Public Credit Registry Coverage**

| Country Name | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | **COUNTRY AVERAGE** | **COUNTRY RANK** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Angola | 1.8 | 2.9 | 2.9 | 2.3 | 2.7 | 2.5 | 2.4 | 1.8 | 1.8 | 2.4 | 1.8 | **2.3** | **15** |
| Burundi | 0.2 | 0.2 | 0.1 | 0.2 | 0.3 | 0.2 | 0.2 | 0.3 | 0.3 | 0.3 | 3.9 | **0.6** | **25** |
| Benin | 0.2 | 3.5 | 10.3 | 7.8 | 10.5 | 10.9 | 10.4 | 10.7 | 10.9 | 10.1 | 10 | **8.7** | **5** |
| Burkina Faso | 0.2 | 1.9 | 2.4 | 2.1 | 1.9 | 1.9 | 1.8 | 1.8 | 1.7 | 2 | 2 | **1.8** | **16** |
| Central African Republic | 0.1 | 1.2 | 1.1 | 1.4 | 1.2 | 2.1 | 2 | 2.2 | 2.4 | 3.1 | 2.6 | **1.8** | **17** |
| Cote d'Ivoire | 0.2 | 3 | 3.1 | 2.8 | 2.9 | 2.7 | 2.6 | 2.6 | 2.9 | 3.2 | 3.2 | **2.7** | **13** |
| Cameroon | 0.1 | 0.8 | 3.4 | 1 | 4.9 | 1.8 | 2.9 | 3.6 | 9.1 | 8.9 | 5.4 | **3.8** | **7** |
| Congo, Rep. | 0.1 | 2.3 | 1.4 | 2.4 | 2.4 | 3 | 2.9 | 8.2 | 8.3 | 9 | 9.4 | **4.5** | **6** |
| Cabo Verde | | 11.9 | 11.9 | 20.3 | 21.8 | 23 | 22.1 | 20.2 | 19.7 | 17.3 | 16.7 | **18.5** | **4** |
| Djibouti | | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.3 | 0.3 | **0.2** | **29** |
| Algeria | 0 | 0 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.3 | 2.3 | 2.4 | 2 | **0.7** | **22** |
| Egypt, Arab Rep. | 1 | 1.2 | 1.5 | 1.7 | 2.2 | 2.5 | 2.9 | 3.5 | 4.3 | 5.3 | 5.8 | **2.9** | **11** |
| Ethiopia | 0 | 0 | 0.1 | 0.1 | 0.1 | 0.1 | 0.1 | 0.2 | 0.1 | 0.1 | 0.2 | **0.1** | **31** |
| Gabon | | 2.6 | 2.6 | 2.4 | 2.4 | 3.9 | 22.5 | 24.2 | 53.8 | 51.1 | 50.8 | **21.6** | **2** |
| Guinea-Bissau | | 1 | 1 | 0.9 | 1 | 1.1 | 1 | 1 | 1.1 | 1.1 | 1 | **1.0** | **18** |
| Equatorial | | 2.4 | 2.4 | 1.9 | 2.7 | 3 | 2.5 | 2.9 | 3.9 | 4.7 | 5.1 | **3.2** | **9** |

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Guinea | | | | | | | | | | | | | |
| Liberia | | | 0 | 0 | 0.3 | 0.3 | 0.2 | 0.6 | 1.1 | 1.4 | 1.7 | **0.6** | **24** |
| Libya | | | | | | | | | 0.5 | 0.5 | 0.5 | **0.5** | **27** |
| Morocco | 0.6 | 2 | 2.3 | 2.3 | 2.4 | 0 | 0 | 0 | 0 | 0 | 0 | **0.9** | **20** |
| Madagascar | 0.3 | 0.3 | 0.3 | 0.1 | 0.1 | 0.1 | 0 | 0.1 | 0.1 | 0.2 | 0.2 | **0.2** | **30** |
| Mali | 0.1 | 2.3 | 2.9 | 2.5 | 4.1 | 4 | 2.9 | 3.7 | 3.3 | 3.7 | 3.6 | **3.0** | **10** |
| Mozambique | 0.5 | 0.8 | 0.7 | 0.9 | 1.9 | 2.3 | 2.2 | 3.8 | 4.4 | 4.3 | 5.7 | **2.5** | **14** |
| Mauritania | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.1 | 0.2 | 0.5 | 1.4 | 4.6 | **0.7** | **22** |
| Mauritius | 0 | 0 | 10.2 | 10.2 | 20.6 | 36.8 | 49.8 | 49.8 | 56.3 | 69.2 | 71.9 | **34.1** | **1** |
| Niger | 0.1 | 0.9 | 1.2 | 1 | 0.9 | 0.9 | 0.7 | 0.9 | 0.8 | 1 | 1 | **0.9** | **21** |
| Nigeria | 0 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0.1 | 0.1 | 0 | 0.1 | **0.0** | **32** |
| Rwanda | 0.1 | 0.1 | 0.2 | 0.2 | 0.3 | 0.4 | 0.7 | 1.4 | 2 | 2.1 | 2.4 | **0.9** | **19** |
| Sudan | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | **0.0** | **33** |
| Senegal | 0.3 | 4.3 | 4.7 | 4 | 4.4 | 4.4 | 3.7 | 4.5 | 4.6 | 1 | 1 | **3.4** | **8** |
| Sierra Leone | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.7 | 0.9 | 1 | **0.2** | **28** |
| Chad | 0 | 0.2 | 0.2 | 0.2 | 0.6 | 0.2 | 0.8 | 0.5 | 0.5 | 0.8 | 2.1 | **0.6** | **26** |
| Togo | 0.3 | 3.5 | 3.6 | 2.7 | 2.6 | 2.7 | 2.5 | 2.5 | 2.8 | 3.1 | 3 | **2.7** | **12** |
| Tunisia | 9.3 | 8.2 | 11.6 | 13.7 | 14.9 | 19.9 | 22.9 | 27.3 | 27.8 | 28.8 | 30.2 | **19.5** | **3** |
| Overall Country Average | | | | | | | | | | | | **4.4** | |

**Source: Computed from World Development Indicators Database**

**2.4 Trends in Public Credit Registry Coverage in Africa.**

Table 2 shows the yearly Public Credit Registry coverage of countries that share credit information through public institutions in Africa. The yearly coverage of public credit registry coverages are summarized by finding the average of public credit bureaus for each country and overall country average from 2004 to 2014.

From the Table 2, 33 countries were identified to share credit information in Africa through public credit registries over the periods under study. Mauritius, Gabon, Tunisia, Cape Vade and Benin recorded the highest Public Credit Registry coverage recording an adult percentage coverage of 34.1%, 21.6%, 19.5%, 18.5% and 8.7% respectively. The table does not shows a strong presence or concentration of Public Credit Registry coverage in Africa as in the case of the private credit bureaus. This indicates that public credit registries are well distributed in Africa over the periods under study. Again, countries that share credit information through public credit registries recorded an average of 4.4% in Africa. This implies that private credit bureaus have a wider coverage in Africa than public credit registries in Africa. Also, it is evident that, more countries share credit information through public credit registries than through private credit bureaus.

From the table, twenty-seven of the countries that sharing credit information through public credit registries representing 81.83% recorded an average below the overall country average. This is an indication that Public Credit Registry coverage is very low in most countries that share credit information through public credit registries. At the country levels, private credit bureau coverage show a consistent and stable growth in private credit bureau coverage in Africa between 2004 and 2014.

Further analysis of the table show that only six countries out of the thirty-three countries that share credit information through public credit registries recorded an average Public Credit Registry coverage above the overall country coverage average. The table further reports that Sudan, Nigeria, Ethiopia, Madagascar and Djibouti are the countries with the least Public Credit Registry coverage in Africa over the period of study. This indicates that the coverage and presence of public credit registries are very low in Eastern Africa.

## 2.5 Conclusion

This chapter presented an overview of the state of credit information sharing through Private Credit Bureaus and Public Credit Registries in the Africa Region. It provided a detail outlook on the state of Africa's credit information sharing schemes using credit information sharing variables such as the depth of credit information sharing, Private Credit Bureau coverage and Public Credit Registry coverage. Tables and figures were used to show rankings and trends.

# CHAPTER THREE

# LITERATURE REVIEW

## 3.1 Introduction

This chapter reviews the theoretical concepts and models that supports the study. It carefully looks at the relevant empirical contributions of previous researchers and their findings. It also elaborates on what others have done and as well position this study differently by way of making meaningful contribution to the subject matter.

## 3.2 Theoretical Concepts and Models Review

This research is supported by the theories of information asymmetry, concepts in adverse selection and moral hazard as well as the theory of credit information sharing.

### 3.2.1 Information Asymmetry

The theory of information asymmetry dates back to Freimer and Gordon (1965) but was expounded by Stiglitz and Weiss (1981). The theory basically postulates that in any transaction involving two parties, one of the parties has superior or more information than the other. This gives the party with superior information an advantage over the counterparty (Bardhan & Udry, 1999) leading to problems of adverse selection and moral hazard. In the seminal work of Stiglitz and Weiss (1981) they postulated that lack of accurate and complete borrowers' information in taking lending decisions may lead to adverse selection and moral hazard as a result of information asymmetry. They further pointed out that taking lending decisions by just focusing on interest and collateral is inadequate, since that may discourage safe borrowers and might encourage risky borrowers which can adversely affect bank performance. However, it was

further argued that asymmetric information within the credit market can as well lead to over lending or excess credit (De Meza & Webb, 1987).

Despite the fact that banks are considered as experts in gathering private information (Freixas & Rochet), and diligent in screening and monitoring borrowers more efficiently (Allen & Santomero, 1997), the theoretical literature review suggests that exchange of credit information between bankers and firm (individuals) are not perfect (Freixas & Rochet, 1997; Myerson, 1991). Thus, banks tend to ration credits in the financial market. However, Stiglitz and Weiss (1981) argue that banks ration credits since they are unable to distinguish between good and bad borrowers, hence they charge a flat rate of interest since cost becomes persistent in selecting borrowers. In this regard, it is not always the case since in real circumstances high risk borrowers are charged high interest rate, and as such credit rationing is less likely to occur. Banks virtually become less efficient in allocating funds to customers or borrowers leaving high non-performing loans sitting on their balance sheets. In an attempt to reduce these non-performing loans or reduce the credit risk, banks adopt various measures including bureaucratic processes and measures to ensure that adequate information about the customers/borrowers are gathered, and use credit information sharing schemes to provide banks with credit histories of potential customers.

### 3.2.2 Credit Information Sharing Theory

The theory of information sharing can be attributable to the works of Pagano and Jappelli (1993). They developed a model with adverse selection which predicts that lenders' incentive to share information about borrowers is positively related to the size of the credit market, and advancement in information technology. The theory highlights that the role the information

exchanges about customers help lenders to mitigate the challenges associated with information asymmetry (Martinez Peria & Singh, 2014) that is adverse selection and moral hazard problems. The theory implies that, sharing information about the past behavior and characteristics of customers can enhance the monitoring and evaluation processes of credit markets to reduce the problems of adverse selection in lending and induce customers to repay loans (Brown, Jappelli & Pagano, 2009).

Besides, sharing information via either public registries or private bureaus reduces the exposure of financial institutions to credit risk, increase asset quality and improve the overall performance and profitability of the institution (Pagano & Jappelli, 1993). Furthermore, Padilla and Pagano (1997) in their study of endogenous communication among lenders and entrepreneurial incentives provides two modes of transmission which attenuates the effects of asymmetric information (Adverse selection & Moral hazard). First, they established that credit information sharing provides opportunities of reputational collaterals and creates an incentive effect. Credit information sharing provide borrowers with higher incentives to perform since information about their credit histories are accessible to all banks and lenders as a goodwill credit record. On the other hand, borrowers are discouraged to default since through information sharing, non-performance on the borrower's side becomes known to other lenders which might result to future denials of credit or high interest rate charges/penalties on credits. Secondly, they added that credit information sharing can also resolve the adverse selection problem through some screening effects, as lenders or bankers take advantage of already existing record of payment histories and credit records to enable them distinguish good borrowers from bad borrowers when taking lending decisions. This supports the view that reputation to a large extent can eventually

deal with the moral hazard problem since better reputation achieved over time implies that adverse selection is less severe (Diamond, 1991).

### 3.2.3 Adverse Selection Theory

The theory of adverse selection which postulates that lenders may select wrong borrowers when granting credit originates from the works of Stiglitz and Weiss (1981). The underlying assumptions of this theory are that banks cannot determine the actual risk profile of borrowers and credit contracts are subject to certain limitations. For instance, a borrower is not required to repay a loan where returns from a project or investment for which the loan was taken is lesser than the debt obligations. In effect, all risks associated with credit contracts accrue to lenders. In response to this, lenders set interest rates to include a risk premium to compensate themselves for the tendency that borrowers will default on their obligations. These high interest rates deter less risky borrowers but attracts borrowers with higher probabilities of defaulting causing lenders to choose the wrong groups of borrowers when extending credit.

### 3.2.4 Moral Hazard Theory

Moral hazard is the probability that deficit units (borrowers) may use funds borrowed for purposes other than those agreed in credit contracts. The theory suggests that unless there are ramifications to future credit applications, borrowers have the tendency to default on their obligations. This emanates from the challenges lenders face in assessing the future wealth of clients or the amounts borrowers would have accumulated on the date loans are to be repaid. In view of this, borrowers may be tempted to invest in riskier ventures which could lead to defaults on loan repayments. Forestalling these uncertainties, lenders increase the rates on loans causing breakdowns in the market (Alary & Gollier, 2001).

### 3.3 Empirical Literature Review

This section reviews previous studies that have been done on the subject areas of credit information sharing through private credit bureaus/credit referencing bureaus and public credit registries, on bank performance as well as bank profitability. It provides us with what previous researchers have done and allow us to position this study distinctly from prevailing ones.

#### 3.3.1 Credit Information Sharing Empirical Review

The impact of credit information sharing has received much attention in recent years especially in developed economies and the emerging economies of Asia and Latin America. Whereas empirical literature on the Africa Region appears to be scanty but nascent, providing little empirical evidence of how credit information sharing schemes can impact the profitability of banks within the Africa Region. Even with the foregoing fact that the Africa banking system is characterized by inadequate credit information sharing, bank inefficiencies and macroeconomic downturns (Honohan & Beck, 2007). However, this review provides some macro, country, firm and bank-level evidence on the impact of credit information sharing on credit risk, loan performance, bank lending volumes, access to finance and the availability of bank credits, cost of credit, bank competition, bank crisis, and overall impact on financial development.

Studies that examine the impact of sharing of credit information on bank credit risk argue in two ways: screening and incentive effects (Brown et al., 2009 and Djankov et al., 2007). First, the screening effect prosits that credit information sharing enables banks evaluate and identify clients ability to service or repay their loans, thereby enhancing the default predictive power of banks and making them more robust against adverse selection (Pagano and Jappelli, 1993). Second, the incentive effect poses that bank customers are moved to reward or service loans

because of the concern of future denial of loan or credit by another lender because default with one lender is seized and shared by all lenders. Hence, bank customers are pressured to perform and settle their loans because of denial of credit in the future upon the default (Padilla and Pagano, 2000).

Pagano and Jappelli (1993) presented a model which revealed that information sharing reduces or counters adverse selection. That is information sharing among lenders allow loans to be advanced to good borrowers who would not have received loans or credit where banks or lenders did not share credit information on borrowers. They found that credit information sharing increases the volume of lending when adverse selection is so severe such that safe borrowers drop out of the market. Their findings seem to support international and historical evidence in the context of consumer credit market in the United States.

Padilla and Pagano (2000) further prove that Credit-sharing institutions using a cross-country macro level test can raise the borrowers' cost of defaulting loans or credit thereby increasing loan repayment by borrowers, and reduce moral hazard. Since sharing default information serve as borrower discipline device, and increase their incentive to perform. They also found that 'fine-tuning' the type and accuracy of information shared by lenders can raise borrowers' incentives to their first-best level. Also Jappelli and Pagano (2002) using a new purpose-built data set from English, French, German, and Scandinavian origins on private credit bureaus and public credit registries, illustrated that credit information increases bank lending volumes and lowers credit risk in countries where lenders share credit information.

Barren and Staten (2003), also provided evidence that lenders can significantly reduce default rates by sharing and involving more complete and in-depth borrower information in their predictive models. Kallberg and Udell (2003), using data set of the world's largest private information broker, Dun & Bradstreet, also pointed out that in the case of US, historical information collated by credit bureaus has powerful default predictive ability, hence making banks more resistant to adverse selection and in turn reducing bank credit risk. Also, Powell et al. (2004) employ banks in Brazil and Argentina and found similar results indicating that more credit information sharing leads to reduced default rates.

Bennardo, Pagano and Piccolo (2010) used an experimental model to show that over-indebtedness can be mitigated through credit information sharing schemes by lenders and banks as individual borrowers classified as highly indebted receive less credit and ultimately reduce the over-indebtedness of borrowers. They concluded that information sharing among banks about clients historical indebtedness lowers interest and default rate, improves access to credit and may act as substitute for creditors rights protection. Other strand of literature (Luoto et al, 2007; de Janvry, McIntosh & Sadoulet, 2010; Hertzberg, Liberti & Paravasini, 2011; Behr & Sonnekalb, 2012; Doblas, Madrid & Minneti 2013) also tried to exploit natural or randomized experiments to estimate the causal effect of credit information sharing schemes on firm credit risk and defaults, yet found similar results.

Studies that investigated the impact of credit information schemes on bank lending volumes and access to finance include papers such as Berger & Frame (2006); Brown, Jappelli & Pagano (2006); Djankov, McLiesh & Shleifer (2007), Gaitho (2013), Fosu (2014) and Martinez & Singh (2014). Berger and Frame (2007) demonstrated that in the US, commercial banks are rapidly

using small business credit-scoring models to underwrite small business credits, and as such increases the amount of loans allocated to small businesses. Brown et al., (2006) find that credit information exchanges between lenders is directly associated with increased and cheaper credits in transition countries in Eastern Europe. Djankov et al., (2007) provided a cross-country evidence to investigate the determinants of private credit using new data set on private and public credit registries in 129 countries. They find that credit information sharing schemes are statistically significant and quantitatively important determinants of private credit development. Credit information institutions is associated with higher ratios of private credit to gross domestic product, while legal origins are salient determinants of credit information sharing schemes. However, they concluded that public credit registries, which are mainly a feature of French civil law countries benefit private credit markets in emerging countries. On the contrary, Behr and Sonnekalb (2012) who used panel regression estimations on 27 Albanian Banks found that credit information schemes are rather more robust in improving loan performance than access to credit. That notwithstanding, a study by Gaitho (2013), on the role of credit reference bureaus on credit access in Kenya also found that private credit bureaus reduces borrowing cost to a moderate extent, since commercial banks can monitor the behavior of borrowers easily.

Despite opposing views, Fosu (2014) focused on the degree of banking market concentration in developing countries to examine the effect of credit information sharing on bank lending. Using bank-level data from 35 African countries on a dynamic two step system generalized method of moments (GMM). He found that credit information sharing significantly increases bank lending, and concluded that the degree of banking market concentration moderates the effect of credit information sharing on bank lending, supporting previous assertions made by some researchers (e.g. Pagano & Jappelli, 1993; Petersen & Rajan, 1995; Jappelli & Pagano, 2002).

Furthermore, Martinez and Singh (2014), in their World Bank Policy Research Paper, extensively studied on 63 countries covering 75000 firms over the period 2002 to 2013, and asserted that credit information schemes increases firm access to finance. The study indicated that Private Credit Bureaus rather than Public Credit Registries, has a significant and robust effect on firm financing, since access to finance increases and interest rate drop after the introduction of credit bureau reforms. They concluded that effects of credit bureau reforms are more pronounced for smaller, less experienced and opaque firms.

Other Strand of literature provide evidence that the credit market would collapse in the absence of reputational banking and credit information sharing (Brown & Zehnder, 2007). That credit information sharing can reduce the likelihood of banking crises (Berrak & Neven, 2012), can lead to higher bank profitability (Houston, Lin, Lin & Man, 2010) or possibly reduce bank profits as a result of persistent competition (Karapetyan & Stacescu, 2014), can as well affect banking system efficiency and financial sector development (Asongu, Nwachukwu & Tchamyou, 2015) and can influence antitrust interventions (Coccorese, 2012).

The African region has shown interesting results, as Asongu et al., (2015), examined the policy threshold of credit information sharing for financial development in 53 African countries over the period 2004 to 2011. Using Generalized Methods of Moments with forward orthogonal deviations, they established that Public Credit Registries and Private Credit Bureaus have negative impacts on financial activity and financial depth, but however found a positive effect on financial size with the effect of Public Credit Registries being greater. They concluded that the establishment of credit information sharing schemes in Africa as a policy on financial development for most part had led to negative effects.

Houston et al., (2010) provides the first international evidence on the influence of credit information sharing on bank profitability, which studies a sample of 2400 banks in 69 countries out of which 14 countries were selected from the Africa Region. They established that the benefits of credit information sharing among lenders (banks) seem to be universally positive, and concluded that greater information sharing leads to higher bank profitability and higher economic growth. However, this assertion made does not provide a clear proposition on the effect of credit information schemes on the profitability of banks in Africa. This research therefore seeks to fill this gap and contribute to the extant literature on the effects of credit information sharing schemes on bank profitability. Taking into consideration the depth of credit information sharing (i.e. the rules/ law and practices affecting the coverage, scope and accessibility of credit information) and the relative effects of Private Credit Bureaus and Public Credit Registries on bank profitability within the Africa Region.

### 3.3.2 Types of Credit Information Sharing Schemes: Public Credit Registry and Private Credit Bureau

In the foregoing literature on credit information sharing, Public registries and Private Credit Bureaus are used as proxies for reducing information asymmetry (Asongu, Nwachukwu & Tchamyou, 2015). These are the two forms of schemes for collecting and sharing credit information on transactions as they provide credit information to mitigate the challenges associated with information asymmetry between lenders (banks) and borrowers. It is not clear whether the relationship between PCRs and PCBs is substitutive or complementary (Han, Lee & Park, 2013). In African, literature suggests that these schemes are usually close substitutes than complements, while private credit bureaus tend to be more efficient and effective than public credit registries (Triki & Gajigo, 2012). Henceforth, the need to critically consider the

distinguishing characteristics of Private Credit Bureaus and Public Credit Registries is paramount to this study, as they could have differing impacts on bank profitability.

Private Credit Bureaus are usually profit oriented information brokers created by the Private Sector, due to demand in the market for reliable credit information on borrowers when the benefits from sharing credit transaction data exceeds the gains to relying solely on the information rent specific to one lender (Pagano & Jappelli, 1993). Public Credit Registries are non-profit agencies created through government policy interventions to supervise the banking sector as part of antitrust policy mechanisms, creditor's right protection and to discipline borrowers (Powell, Mylenk, Miller & Majnoni, 2004; Jappelli & Pagano, 1999). Hence the participation of banks in credit information exchanges through Public Credit Registries is obligatory or mandatory (Jappelli & Pagano, 2002), which is not the case for Private Credit Bureaus; where information sharing is voluntary. Most importantly, the promotion of stability and competition within the banking system constitutes the establishment of Public Credit Registries (Jappelli & Pagano, 1993), and not Private Credit Bureaus.

The coverage of these schemes in terms of scope, source of information and type of credit information stored within their databases also indicates a clear distinction. According to Triki and Gajigo (2012), the coverage offered by Private Credit Bureaus is more likely to be more comprehensive than Public Credit Registries since the latter focuses usually on transactions of financial institutions supervised by government, while the former is broad and diverse in scope taking credit histories of individuals and firms from tax authorities, banks and non-banking financial institution, courts, utilities and retailers (Miller, 2003). However, the credit information available through Public Credit Registries is restricted to information providers, whiles in the

case of Private Credit Bureaus it is open to all types of lenders. The table below shows a summary of some key distinguishing characteristics between Public Credit Registries and Private Credit Bureaus.

**Table 3: Differences: Public Credit Registry & Private Credit Registry**

| | **Public Credit Registry** | **Private Credit Bureau** |
|---|---|---|
| **Purpose** | Banking supervision (usually antitrust policy) | Sharing of credit information to help lenders take informed decisions |
| **Coverage** | Mainly large corporate. Limited in terms of history and type of data provided. | Large corporations, SMEs, individuals. Longer history and more rich data provided. |
| **Ownership** | Government or central banks | Government/central banks, lenders, lenders' associations, independent third parties |
| **Status** | Non - profit | usually for profit |
| **Data sources used** | Banks and non-banks financial institutions | Banks, non-banks financial institutions, PCRs, tax authorities, courts, utilities |
| **Accessibility** | Restricted to information providers | Open to all types of lenders |

### 3.4 Bank Profitability Empirical Review

This section reviews selected studies on the determinants of bank profitability from the banking and financial literature. Studies on bank profitability have principally employed Return on Assets (ROAA), Net Interest Margin (NIM) and Return on Equity (ROE) as common measures. Empirical Studies suggest that bank specific, industry and macroeconomic factors affects the profitability of banks (Short, 1979; Smirlock, 1985; Bourke, 1989; Molyneux & Thorton, 1992;

Demirguc-kunt & Huizinga, 1999, Staikouras & Wood, 2003; Goddard et al., 2004; Pasiouras & Kosmidou, 2007; Athanasoglou, Sophocles & Delis 2008; Berger & Bouwman, 2009; Kasman, 2010; Curak, Poposki & Pepur, 2012; Francis, 2013; Vejzagic & Zarafat, 2014, Tan, 2015 etc.). However, the aforementioned authors who studied on bank profitability did not consider how the reduction of information asymmetry through credit information sharing can influence the profitability of banks. This research gap is what the study seeks to fill using credit information sharing schemes to proxy the reduction of asymmetric information to provide evidence for the African banking system.

### 3.4.1 Bank Specific Determinants, Industry and Macroeconomic Determinants

Bank specific determinants are internal factors as they arise from within the bank. Some of which includes bank size, capital holdings (capital adequacy), financial risk (liquidity and credit risk), cost management (managerial or operational efficiency), share of interest income, bank ownership. Industry and macroeconomic determinants are referred to as External determinants of bank profitability. Some of these factors include Inflation rate, taxation, Gross Domestic Product per capita and other variables of market characteristic such as bank concentration. Among these factors, researchers have provided myriad views based on some theories (signaling theory, expected bankruptcy cost hypothesis, risk-return hypothesis, efficiency structure and market power hypothesis, economic of scale, regulatory theory etc.) and suggestions depending on their scope of study; cross-country, country specific and regional blocs. For example Dietrich and Wanzenreid (2014), showed that profitability determinants vary across different income level countries (low, middle and high income countries). They used the GMM estimator technique to analyze bank specific, industry and macroeconomic variables that affect the profitability of 10,

165 commercial banks across 188 countries. Hitherto, there is however limited study on the Africa Region.

A study by Alexiou and Sofoklis (2009) on the determinants of bank profitability in the Greek banking sector, used an empirical framework that incorporates the traditional structure performance conduct and found that bank specific determinants (bank size, credit risk, bank efficiency, liquidity) significantly influence bank profitability, but indicates an ambiguous picture when macroeconomic factors (gross domestic product, inflation, private consumption) were considered. This provides support to the study by Al-Hashimi (2007), who employed an accounting decomposition model and a panel regression on banks in 10 Sub-Saharan Africa countries indicating that macroeconomic factors have less impact on bank profitability.

However, the study by Francis (2013) using a panel data on banks in 42 Sub-Saharan Africa countries found that capital adequacy, liquidity risk, bank size, operational efficiency, inflation and growth in gross domestic product have significant impact on bank profitability using Return on Asset as a proxy. Petria, Capraru and Ihnatov (2015), also examined the factors influencing the profitability of banks in 27 European Union countries for the period 2004 to 2011 and found that diversification of business also matters to bank profitability, similar to the findings by Dietrich and Wanzenried, 2014. They concluded that diversification of business and economic growth has influence on both Return on Average Asset and Return on Average Equity. Tan (2015) extended the literature to include taxation, labor productivity and overhead costs to study their influence on bank profitability in China from 2003 to 2011, and found significant impacts on their profitability levels following the works of previous scholars and researchers (Bourke,

1989; Molyneux & Thornton; Anthanosoglou, Delis & Staikouras 2006) that expense related variables are key variable in a profit function.

### 3.5 Conclusion

Chapter three reviewed all possible theories, concepts and empirical studies which support the subject matter understudy. These include Information asymmetry theory, credit information sharing, adverse selection, moral hazard and bank profitability. The chapter also deliberated on the differing characteristics of Private Credit Bureaus and Public Credit Registries as the study anticipates their diverse impacts on bank profitability.The chapter found limited study on the impact of credit information sharing schemes on the profitability of banks within the Africa Region, and provides the motivation to assess how the reduction in information asymmetry could influence bank profitability.

# CHAPTER FOUR

# METHODOLOGY

## 4.1 Introduction

This chapter describes the procedures and research methodologies used in the study. It shows the form of study conducted, research methods and justify reasons for using such methods in answering the research questions. Specifically, the chapter highlights the model specification for the study, define the variables specified in the model and provide justifications. The sample, source of data, the data analysis tool and techniques are also explained into details.

## 4.2 Research Design

The study employs a quantitative research design, since it helps to understand the best predictors of outcomes (Creswell, 2012). The results of quantitative research are independent of the researcher as it requires rigorous processes and procedures which limits the influence of the researcher, and depicts the true state of affairs of the phenomenon understudy (Yauch & Stendel, 2003). However, it is challenged with detailed report on individual specific issues (Dudwick, Kuehnast, Jones & Woolcock, 2006).

A panel data methodology is used in this study, as the study comprises recurrent observations on the same cross section of units over time (Wooldridge, 2012). According to Baltagi (2008), this methodology is more informative, affords more degree of freedom and less collinearity among independent variables. Furthermore, panel dataset controls for cross-sectional unobserved heterogeneity, which ignored can lead to biased results (Brooks, 2008).

### 4.3 Sampling and Source of Data

The population of the study entails banks operating within the African continent. A sample data of banks within 41 African countries, covering the years 2004 to 2013 is purposively drawn from financial statements of individual banks provided in the Bank Scope Database. Only banks in African countries that use credit informations schemes were selected, and only countries that has credit information infrastructure or schemes were selected. The bankscope Database is a collection of data of balance sheets, income statements and other relevant financial accounts of several banks in the world. Banks with negative values of equity, and with missing dependent variable (ROAA) are also dropped (see Fosu, 2014). In addition, the study uses secondary data from the World Bank Database – World Development Indicators for macroeconomic measures, where some data points were also missing. Hence, an unbalanced panel approach was adopted.

### 4.4 Model Specification

The study seeks to empirically determine the impact of credit information sharing schemes (in relation to its coverage, scope, quality, accessibility) on the profitability of banks for the period from 2004 to 2013.The study assumes the use of panel analytical methods to realize the set objectives. The importance of understanding the factors behind the time series variation in macroeconomic data, alongside those that shape the bank data variation, cannot be overemphasized. Given the significance of time series variation in macroeconomic data in modern times, an empirical investigation into the impact of credit information sharing schemes on bank profitability must be able to account for variation both across bank and overtime. Panel data estimation controls for omitted variables and bank specific effects and also allow for both long and short run effects thereby overcoming the inadequacies of cross-sectional and time series estimation technique (Stock &Watson, 2001).

Therefore the study employs panel data techniques to shed light on the effects or contributions if any, of credit information sharing schemes on bank profitability in the African region, as it controls for bank specific, industry and macroeconomic effects.

The general form of a panel data model is $Y_{it} = \mu_i + \gamma_t + \beta X_{it} + v_{it}$ … **(1)**

Where: Subscript *i* denotes the cross-sectional dimension (bank in a country) i=1. . . *N* and t denotes the time series dimension (time), t=1…T;

- $Y_{it}$ is the dependent variable.
- $\boldsymbol{\mu_i}$ is scalar and constant term for all periods (t) and specific to a bank fixed effect (*i*).
- $\boldsymbol{\gamma_t}$ is the time fixed effect t.
- $\beta$ is *a k*×1 vector of parameters to be estimated on the independent variables or the factor loadings or parameter estimates for the explanatory variables.
- $X_{it}$ is *a 1*× k vector of observations on the independent variables comprising of independent variables in the model which includes controlled variables.
- $v_{it}$ is the error term (*iid - Independently Identically Distributed*).

From the econometric point of view, the specific models are stated as:

$$\mathbf{ROAA_{it} = \beta_1 CID_t + \beta_2 LnTA_{it} + \beta_3 ETA_{it} + \beta_4 NPLsratio_{it} + \beta_5 CTIR_{it} + \beta_6 LTA_{it} + \beta_7 HHI_t + \beta_8 CPI_t + \beta_9 GDPG_t + \varepsilon_{it} \ldots (2)}$$

$$\mathbf{ROAA_{it} = \alpha_1 PCB_t + \alpha_2 LnTA_{it} + \alpha_3 ETA_{it} + \alpha_4 NPLsratio_{it} + \alpha_5 CTIR_{it} + \alpha_6 LTA_{it} + \alpha_7 HHI_t + \alpha_8 CPI_t + \alpha_9 GDPG_t + \varphi_{it} \ldots (3a)}$$

$$\mathbf{ROAA_{it} = \gamma_1 PCR_t + \gamma_2 LnTA_{it} + \gamma_3 ETA_{it} + \gamma_4 NPLsratio_{it} + \gamma_5 CTIR_{it} + \gamma_6 LTA_{it} + \gamma_7 HHI_t + \gamma_8 CPI_t + \gamma_9 GDPG_t + v_{it} \ldots (3b)}$$

***Where*: $\varepsilon_{it}$, $\varphi_{it}$, $v_{it}$ *have firm specific and time specific components, and are independent and identically distributed***

### 4.5 Variable Selection and Justification for Bank Profitability (ROAA)

This section defines and provides justifications for the selected variate and covariates in the model specified above. It also provide information on how each variable is measured, source of variable and expected signs.

#### 4.5.1 Variate for Bank Profitability (ROAA)

In the finance literature (Dietrich and Wanzenried, 2011; Anthanasoglou et al., 2008; Pasiouras and Kosmidou, 2007; Golin, 2001; Demirguc-Kunt and Huizinga, 1999) the common profitability measurements explored are the traditional accounting measure (Return on Assets – ROA, ROE and NIM) and the non-traditional measures (Economic Value Added – EVA, Market Value Added – MVA and Risk Adjusted Return on Capital). According to Goddard et al. (2004), the traditional profit measures are flexible to compute but the computation of economic profitability measurements are difficult due to lack of internal information disclosure. And further argues for the use of ROA instead of ROE since ROE ignores financial leverage (Deitrich & Wanzenried, 2011; Athanasoglou et al., 2008).

ROA is measured as net income divided by total assets. However, the use of average yearly values of asset expresses profitability more accurately than the end year values. Thus, the study uses ROAA measured as net profit divided by average asset (expressed in %) following (Deitrich & Wanzenried, 2014; Golin & Delhaise, 2013).

### 4.5.2 Covariates for Bank Profitability

This section provides definitions and justifications for the selected explanatory variables for bank profitability. It includes the expected signs in relation to previous theoretical and empirical studies.

#### *4.5.2.1 Depth of Credit Information Sharing (CID)*

Credit Information Sharing Schemes is deemed to have a positive relationship on bank profitability (Houston et al., 2010; Barren & Staten, 2003).The study employs the depth of credit information index (developed by Djankov, Mcliesh and Shleifer, 2007), which has been adopted by only three studies (Fosu, 2014; Berrak & Neven, 2012; Houston et al., 2010). It does not just measure the existence of credit information sharing schemes, but the depth of credit information sharing schemes (Fosu, 2014). It measures the rules and practices affecting the coverage, scope and accessibility of credit information available through either a credit bureau or a credit registry (World Bank, 2015 - World Development Indicators). The index ranges from 0 to 8, with higher values indicating the availability of more credit information, from either a credit bureau or a credit registry, to facilitate lending decisions. If the credit bureau or registry is not operational or covers less than 5% of the adult population, the score on the depth of credit information index is 0. A score of 1 is assigned for each of the following eight features of the credit bureau or credit registry (or both):

- Data on both firms and individuals are distributed.
- Both positive credit information (for example, original loan amounts, outstanding loan amounts and a pattern of on-time repayments) and negative information (for example, late payments and the number and amount of defaults) are distributed.

- Data from retailers or utility companies are distributed in addition to data from financial institutions.
- At least two years of historical data are distributed. Credit bureaus and registries that erase data on defaults as soon as they are repaid or distribute negative information more than 10 years after defaults are repaid receive a score of 0 for this component.
- Data on loan amounts below 1% of income per capita are distributed.
- By law, borrowers have the right to access their data in the largest credit bureau or registry in the economy. Credit bureaus and registries that charge more than 1% of income per capita for borrowers to inspect their data receive a score of 0 for this component.
- Banks and other financial institutions have online access to the credit information (for example, through a web interface, a system-to-system connection or both).
- Bureau or registry credit scores are offered as a value added service to help banks and other financial institutions assess the creditworthiness of borrowers.

#### *4.5.2.2 Private Credit Bureau (PCRB) & Public Credit Registry (PCRR)*

A private credit bureau is defined as a private firm or non-profit organization that maintains a database on the creditworthiness of borrowers (individuals or firms) in the financial system and facilitates the exchange of credit information among creditors, while credit registry is a database managed by the public sector (central banks or the superintendent of banks). Many credit bureaus support banking and overall financial supervision activities in practice, though this is not their primary objective. Credit investigative bureaus that do not directly facilitate information exchange among banks and other financial institutions are not considered.

This study proxies the existence and credit information shared through Private Credit Bureau and Public Credit Registry with credit bureau coverage and credit registry coverage respectively (Following Houston et al., 2010). It reports the number of credit histories of individuals and firms listed in a credit bureau's database/credit registry. The number is expressed as a percentage of the adult population and if no credit bureau/registry operates, the coverage value is 0.0% (World Bank's World *Development Indicators).*The study anticipates private credit bureaus to be more effective and comprehensive in information coverage in reducing information asymmetry (Miller, 2003); expecting to have a positive significant impact on profitability, since credit bureaus have higher coverage and scope than public credit registries (see Triki & Gajigo, 2012; Love & Mylenko, 2003; Kallberge & Udell, 2003; Miller, 2003; Galindo & Miller, 2001). On the other hand, the study anticipates a negative relationship between credit information shared through Public Credit Registries and bank profitability, since PCRs are used as government antitrust to mechanisms to boost competition through declines in informational rents advantages within the banking system, which might reduce profitability as a result of a fall in interest rate charges (Karapetyan & Stacesu, 2014).

#### *4.5.2.3 Bank Size (LnTA)*

The study employs bank size as an internal or banks specific determinant of bank profitability which captures potential economies or diseconomies of scale in the banking sector. Bank size is measured as the natural log of total asset. It controls for cost differences, and product and risk diversification (Athanasoglou et al., 2005). However, the expected sign appears to be ambiguous (Athanasoglou et al., 2008): Following studies (Jabbar, 2014, Goddard et al., 2004, Bikker and

Hu, 2002,) that concur size influences profitability positively, if there is a significant economies of scale, whiles other studies (Acaravci and Calim, 2013; Kasman, 2010; Stiroh and Rumble, 2006) provide evidence for (diseconomies of scale) a negative relationship on profitability as increased risk diversification could lead to lower credit risk and thus reduce returns.

#### *4.5.2.3 Capital Adequacy (ETA)*

This study controls for the leverage structure of the banking system (following Athanasoglou et al., 2008; Iannota, Nocera & Sironi, 2007) by using the equity to asset ratio (a converse of the leverage ratio). Equity to asset ratio is used to proxy for Capital Adequacy, which estimates how much of assets are financed with owner's capital or equity. The ability of a bank to absorb losses (bankruptcy) depends on their capital strengths. However, the relationship of this variable and bank profitability is mixed and inconclusive. A study on the signaling hypothesis and bankruptcy cost hypothesis; Berger (1995), infers that high equity to asset ratio increases profitability because of lower cost of financial distress, indicating a positive relationship between capital and bank profitability. Athanasoglou et al., (2008) also found a positive significant effect of capital on bank profitability showing a sound financial position for Greek banks since banks with higher equity to asset ratios normally have reduced needs for external funding (Dietrich & Wanzenried, 2014). Conversely, the conventional risk-return hypothesis imply a negative relationship between equity to asset ratio and bank profitability.

#### *4.5.2.4 Credit Risk (NPLs ratio)*

Variations in credit risk largely reflect changes in the soundness of a bank's loan portfolio (Cooper et al., 2003). Non-performing Loans to Gross Loans is used to proxy for credit risk in

the study (following Francis, 2013). An increased exposure to credit risk is associated with decreased bank profitability. A high level of this indicator implies a significant deterioration of banks' assets which leads to a decrease in bank profitability. We expect a negative relationship with this variable on bank profitability.

#### *4.5.2.5 Management/Operational efficiency (CTIR)*

The study use the cost to income ratio as a proxy for bank management efficiency. Following Pasioras and Kosmidou (2007), it is expressed as the operating costs (staff, salaries, and property costs, administrative cost, excluding losses due to bad and non-performing loans) over total generated revenue. This variable shows how expensive it is for a bank to produce a unit of operating income in terms of costs not related to interest expense. We expect higher cost to income ratio to have an inverse relationship with profitability.

#### *4.5.2.6 Liquidity (LTA)*

The study introduces the Loan to total asset ratio as a measure of liquidity and lending specialization (following Chronopolous et al., 2015). The higher the ratio, the lower the bank liquidity. It provides informational advantages, which may lower intermediation costs and improve profitability (Freixas, 2005). Bank profitability is sensitive to its liquidity position as banks with comparatively high loan to asset ratio expects to be more likely to sustain losses if a "fire-sale" of assets is required to meet liquidity needs (Berger et al, 2005).This implies a negative relationship with bank profitability. However, Berger and Bouwman (2009) indicated a positive impact of liquidity on the value of banks since an increase in bank loans can trigger an increase in interest incomes. Clearly, the relationship between this indicator and bank

profitability is uncertain, as empirical studies provide mixed results. A priori there is no clear expectation on the relationship between this control variable and profitability.

#### *4.5.2.7 Bank Concentration (HHI)*

The study controls for bank concentration, an industry specific factor, proxied by the Herfindhal-Hirschman Index (HHI) on loans (see Sufian & Chong, 2008). HHI is calculated as the sum of squares of the market share of banks. It is a proper concentration index because it accounts for the share of each bank in the market and gives higher weight to firms with larger market shares. The overall effect of bank concentration on profitability is mixed and inconclusive (see Berger 1995, Berger et al., 2004). Studies by Molyneux and Thornton (1992) that bear out the Structure-Conduct Performance show positive impact to profitability, while others (Demirguc-kunt & Huizinga, 1999; Staikouras & Wood, 2004) that support the Efficiency Structure hypothesis provides opposite results.

#### *4.5.2.7 Inflation (CPI)*

The study controls for inflation, a macroeconomic variable which is deemed to explain some variations in bank profitability. The Consumer Price Index (based on the laspeyres formula) is used to proxy for inflation. It reflects the annual percentage changes in the cost to average consumer of acquiring a basket of good and service that may be fixed or changed at specified intervals, such as yearly ( see Vejzagic & Zarafat, 2014). Bank profitability is responsive to inflation such that if banks' income rises rapidly than its cost, inflation is anticipated to exert a positive effect on profitability (Demirguc-Kunt & Huizinga, 1999; Molyneux & Thornton, 1992; Bourke, 1989).This is the case where banks completely project inflation rate and make

appropriate adjustments to interest rates in order to increase revenue. On the other hand, an inverse relationship is expected when bank costs increase faster than its income. In the case of imperfect interest rate adjustment as a result of unexpected changes in bank cost.

#### *4.5.2.8 Real Gross Domestic Growth (GDPG)*

The study employs real Gross Domestic Product growth as one of the macroeconomic variables to control for cyclical output effect (following Acaravci & Calim, 2013). The study expects a direct relationship between GDP growth and bank profitability as banks prospectively have more business opportunities during buoyant economic conditions (Albertazzi & Gambacorta, 2009).This is because higher economic growth may lead to greater demand for both interest and non-interest activities, and provides opportunity for lower default, thereby improving the profitability of banks. However, during recessions or economic downturns, bank profitability relatively since clients have difficulties in settling their loans (high default risk).

**Table 4: Summary of Variables for Bank Profitability**

| Symbol | Variables | Type/Proxy | Expected relation | Source of data |
|---|---|---|---|---|
| **ROAA** | Return on Average Asset | **Dependent Variable**<br><br>Net profit/average Asset | | Bankscope |
| **CID** | Depth of Credit Information Sharing Index | **Information Sharing Variable: Independent**<br><br>Take into consideration the overall effectiveness of the credit sharing information scheme: in terms of scope, coverage and accessibility of credit information. It measures the rules/laws affecting the coverage, scope and accessibility of credit information shared<br><br>Index range ( 0 – 8) | + | World Bank Data - WDI |
| **PCB**<br><br>**PCR** | Private Credit Bureau<br><br>& Public Credit Registry coverage | **Information Sharing Variable: Independent Variable**<br><br>A measure of credit information coverage by Private Credit Bureaus and Public Registries respectively. Reports the number of credit histories of individuals and firms listed in a private credit bureau's database/public credit registry expresses as a percentage of the adult population (%). | +<br><br>– | World Bank Data – WDI |
| **LnTA** | Bank Size | **Bank Specific Variable**<br><br>Logarithm of Total Assets (log) | +/- | Bankscope |

| | | | | |
|---|---|---|---|---|
| **ETA** | Capital adequacy | **Bank Specific Variable**<br><br>Equity/Total Assets (%) | +/- | Bankscope |
| **NPLsratio** | Credit Risk | **Bank Specific Variable**<br><br>Impaired Loans (NPLS)/Gross Loans (%) | - | Bankscope |
| **CTIR** | Management Efficiency | **Bank Specific Variable**<br><br>Operational Cost/ total generated revenue (%) | - | Bankscope |
| **LTA** | Liquidity Risk | **Bank Specific Variable**<br><br>Loans/Total Assets (%) | +/- | Bankscope |
| **HHI** | Bank Concentration | **Industry Specific Variable**<br><br>Herfindhal - Hirshman Index (Loan) | +/- | Computed by Author based on data from Bankscope |
| **CPI** | Inflation | **Macroeconomic Variable**<br><br>Consumer Price Index (%) | +/- | World Bank Data – WDI |
| **GDPG** | Economic Growth | **Macroeconomic Variable**<br><br>Yearly real GDP Growth rate (%) | + | World Bank Data – WDI |

### 4.6 Estimation Strategy

The Ordinary Least Square Estimator is the simplest way to estimate the coefficients in the specified model. However, the technique to estimate the model depends on how the composite error term is structured, and the correlation between the error term and the explanatory variables.

Conversely, the pooled OLS estimation for panel assumes that observations are uncorrelated across individual and time, and expects the number of observations across time (t) and individuals (i) to be at least as large as the total number of individuals observed.

The diagnostic test prove that the OLS estimator is not BLUE (Best Linear Unbiased Estimator) for the data understudy ( see Appendix 3: A, B, C). The Gauss – Markov theorem suggest that, the OLS will be BLUE when there are no complexities of autocorrelation and heteroscedasticity: the OLS estimator becomes inconsistent, bias and inefficient if any of such exist (Brooks, 2008). The Shapiro - Wilk (SW) test for normality (in Appendix 1) show that the error term is normally distributed, and the Wooldridge test for autocorrelation (in Appendix 2: A, B, C) show that no first-order autocorrelation exist. Conversely, the error term is found to be heteroscedastic using Breusch-Pagan / Cook-Weisberg test (in Appendix 3: A, B, C).

Therefore, the study adopts the Generalized Least Square approach, specifically the Fixed Effect and the Random Effect Estimation Strategy (see Appendix 4: A, B, C & Appendix5: A, B, C respectively). Subsequently, the selection of either Fixed or Random effects depends on the Hausman tests (Baltagi, 2001). The Hausman specification test (Hausman, 1978) concludes whether the estimates of the coefficients, taken as a group are significantly different from the two regressions (fixed effects and random effects). The null hypothesis (difference in coefficients is not systematic) in the Hausman test is that the preferred model is random effect as opposed to the alternative hypothesis (difference in coefficient is systematic) which says the preferred model is the fixed effect.

In this study (see Appendix 6: A, B, C) the Hausman test indicates that the difference in coefficients between the fixed effect and the random effect is systematic, selecting fixed effects model over the random effects model with p-values (Prob>chi2=0.0000). Finally, the study adopts a robust fixed effect estimation approach which corrects for standard errors as a result of heteroscedasticity to alleviate biasness in the coefficients.

### 4.7 Conclusion

This chapter provided thorough explanation of the methods adopted in realizing the objectives of the study. The chapter focused on the research design employed for the study and provided the source of secondary data. Further, the chapter pointed out the variables selected in the study and justified reasons for their selection. Finally, the chapter highlighted estimation strategies that may be relevant for this study.

# CHAPTER FIVE

# RESULTS AND DISCUSSION OF FINDINGS

## 5.1 Introduction

This chapter provides the results derived from analyzing the data set for the study. It presents the descriptive statistics of all variables used in the study. The linear relationship among the variables are also highlighted using the correlation matrix. The chapter also presents and discusses the empirical findings of the econometric model adopted for estimation.

## 5.2 Data Analysis and Presentation

This section gives the descriptive summary statistics of the dataset used for the analysis and provides the correlation analysis for the covariates used in examining bank profitability in the Africa banking system for the period 2004 to 2013.

### 5.2.1 Descriptive Statistics

**Table 5: Descriptive Summary Statistics on Bank Profitability Data**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| | | | | | |
| **ROAA*** | 3633 | 1.81 | 7.47 | -315.47 | 139.72 |
| **lnTA** | 4041 | 13.00 | 1.98 | 4.39 | 19.12 |
| **ETA*** | 4009 | 16.84 | 15.78 | 0.01 | 100.00 |
| **NPLsratio*** | 2129 | 8.76 | 10.44 | 0.01 | 79.90 |
| **CTIR*** | 3885 | 63.05 | 30.87 | 0.37 | 313.74 |
| | | | | | |
| **lTA*** | 3775 | 51.53 | 20.63 | 0.53 | 98.48 |
| **HHI** | 4041 | 0.21 | 0.14 | 0.09 | 0.90 |
| **CPI*** | 3613 | 131.96 | 31.75 | 24.87 | 223.00 |

| | | | | | |
|---|---|---|---|---|---|
| **GDPG*** | 3689 | 5.16 | 3.66 | -16.16 | 38.00 |
| **CID** | 4041 | 1.67 | 2.45 | 0.00 | 8.00 |
| | | | | | |
| **PCB*** | 4041 | 10.07 | 19.75 | 0.00 | 66.20 |
| **PCR*** | 4041 | 3.46 | 9.26 | 0.00 | 69.20 |

***Source: Computation on financial data of banks in 41 African countries, Collected from Bankscope Database and WDI.***

***NB: Variables in asterisks (*) are in percentages (%). ROAA: Return on Average Asset (Bank Profitability), lnTA: natural log of Total Assets(bank Size), ETA: Equity to Total assets(Capital Adequacy), NPLsratio: Impaired loans to Gross Loans(credit risk), CTIR: Cost to Income Ratio(Management Efficiency), lTA: Loan to Total Asset(liquidity risk), HHI: Herfindhal - Hirshman Index(Loan – Bank Concentration),CPI: Consumer Price Index(Inflation),GDPG: Real Gross Domestic Growth rate, CID: Depth of Credit Information Index (Credit Information Sharing Scheme), PCB: Private Credit Bureau(Coverage), PCR: Public Credit Registry(Coverage)***

Table 5 above presents the summary statistics of the variables used in this study from 2004 to 2013. It reports the mean, standard deviation, minimum and maximum values of the variables understudy. The SW Test (see Appendix 1) was used to check whether the variables are normally distributed around the mean. The SW test confirms that all the variables were normally distributed around their mean.

Bank profitability (ROAA) employed as the outcome variable has a mean of 1.81%, minimum and maximum of minus 315% and 139.72% respectively, indicating that on the average banks have the tendency of lower levels of profitability which could probably be as a result of low depth of credit information sharing schemes (*CID*: Mean=1.67), low levels of growth in asset (lnTA: Mean =13.00), low levels of capitalization (ETA: Mean =16.84%), high cost of operations/ operational inefficiency (CTIR: Mean = 63.05%), High levels of illiquidity (lTA:

Mean = 51.53%), poor macroeconomic environment characterized by low growth in GDP ( GDPG: Mean=5.16%) and High inflation pressures (CPI: Mean = 131.96%).

The variable of interest, depth of credit information sharing index (CID) has a standard deviation of 2.45, with minimum of 0.00 and maximum of 8.00. This indicates that some banks in the Africa Region might have high access to more credit information to facilitate lending decisions to enhance profits, while others have no accesses to credit information sharing schemes during the period of study. Also, the Table indicates that on the average, Private Credit Bureaus (PCB) have a relatively higher coverage in credit information than Public Credit Registries (PCR) in the Africa Region. Since Private Credit Bureau represents a mean coverage of 10.07% out of the adult population (with minimum point of 0.00% and a maximum point of 66.20%) against a mean coverage of 3.46% out of the adult population for Public Credit Registry (with minimum point of 0.00% and a maximum of 69.20%). This could imply that Private Credit Bureaus are wider in scope in term of providing a detail credit information/history on individuals and firms than Public Credit Registries.

### 5.2.2 Correlation Matrix

Table 6 below depicts the correlation which indicates the linear relationship among the variables used in the study. The correlation coefficients explained in the Pearson correlation below reports the direction and magnitude of the relationship that exist between two variable but does not indicate which variable influences the other (direction of causality). The sign indicates the direction of the relationship while the magnitude of relationship is determined by taking the absolute value of the coefficient. The Pearson's correlation matrix also serves as a test for collinearity of each variable compared with other variables needed to achieve the set objectives.

The study sets an arbitrary threshold of 0.7 for the Pearson's correlation to be considered as the existence of high collinearity between a variable and other variables (see Kennedy, 2008), and further employs the Variance Inflation Factor (VIF) to check for multicollinearity following a rule of thumb where VIF values are less than 10 (VIF$i$ < 10), which is an indicative of inconsequential collinearity (see Hair et al., 1995; O'Brien, 2007). The diagnostic test (see Appendix 7) using the VIF to check for multicollinearity show that the VIF values of all predictors in the model are less than 10, indicating no multicollinearity.

**Table 6: Pearson Correlation Matrix**

| | ROAA | CID | PCR | PCB | lnTA | ETA | NPLsratio | CTIR | lTA | HHI | CPI | GDPG |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | |
| **ROAA** | 1 | | | | | | | | | | | |
| **CID** | 0.05*** | 1 | | | | | | | | | | |
| **PCR** | -0.04** | 0.23*** | 1 | | | | | | | | | |
| **PCB** | 0.09*** | 0.73*** | -0.18*** | 1 | | | | | | | | |
| **lnTA** | 0.07*** | 0.34*** | 0.07*** | 0.26 | 1 | | | | | | | |
| **ETA** | 0.25*** | 0.08*** | -0.03** | 0.15*** | -0.32*** | 1 | | | | | | |
| **NPLsratio** | -0.21*** | -0.02 | -0.01 | -0.10*** | -0.16*** | 0.12*** | 1 | | | | | |
| **CTIR** | -0.25*** | -0.09*** | -0.07*** | -0.03** | -0.32*** | 0.08*** | 0.16*** | 1 | | | | |
| **lTA** | 0.02 | 0.21*** | 0.17*** | 0.17*** | -0.01 | -0.07*** | -0.06** | -0.06*** | 1 | | | |
| **HHI** | -0.08*** | -0.30*** | 0.01 | -0.26*** | -0.19*** | -0.04** | 0.03 | 0.07*** | -0.13*** | 1 | | |
| **CPI** | 0.04** | 0.07*** | -0.05*** | 0.03* | 0.07*** | 0.05*** | -0.02 | 0.04** | -0.09*** | -0.22*** | 1 | |
| **GDPG** | 0.06*** | -0.27*** | -0.13*** | -0.20*** | -0.12*** | -0.02*** | -0.01 | 0.03 | -0.10*** | 0.08*** | -0.03* | 1 |
| | | | | | | | | | | | | |

**Note: ***, **, *, indicates significance at 1%, 5% and 10% levels respectively**

***ROAA: Return on Average Asset (Bank Profitability), lnTA: natural log of Total Assets(bank Size), ETA: Equity to Total assets(Capital Adequacy), NPLsratio: Impaired loans to Gross Loans(credit risk), CTIR: Cost to Income Ratio(Management Efficiency), lTA: Loan to Total Asset(liquidity risk), HHI: Herfindhal - Hirshman Index(Loan-Bank Concentration), CPI: Consumer Price Index(Inflation), GDPG: Real Gross Domestic Growth rate, CID: Depth of Credit Information Index (Credit Information Sharing Scheme), PCB: Private Credit Bureau(Coverage), PCR: Public Credit Registry(Coverage)***

The Pearson Correlation matrix also provides interesting associations between the credit information sharing scheme variables (thus the Depth of credit information index - *CID*, Private Credit Bureau (Coverage) – *PCB* and the Public Credit Registry (Coverage) – PCR) used in this study. The results show a correlation coefficient of 0.73 at 1% level of significance, implying a strong positive degree of association between the depth of credit information index and the private credit bureau coverage (i.e. credit information shared through PCB's). The degree of association between the Public Credit Registry coverage and the depth of credit information show a weak positive correlation (0.23 at 1% level of significance). It can be inferred from the above that Private Credit Bureaus are more strongly associated with high magnitude in-depth (scope, coverage, quality and accessibility) of credit information than Public Credit Registries (see Jappelli and Pagano, 2000). Moreover, the results in Table 6 show an inverse or negative relationship between Private Credit Bureau and Public Credit Registries (with correlation coefficient of – 0.18 at 1% level of significance), which intuitively suggest that the two credit information sharing schemes are substitutes and significantly diverse in operation. However, the substitutability between PCB and PCR cannot be exaggerated, since the two schemes of information sharing may be complements (see Jappelli and Pagano, 2000).

### 5.3 Empirical Results

As discussed in chapter four (section 4.6), this section shows the Robust Fixed Effect regression results of the impact of the depth of credit information sharing schemes (CID), as well as private credit bureau (PCB) and public credit registry (PCR) coverage on the profitability of banks within 41 African countries (Appendix 8), over the 10 - year period (2004 – 2013). The study employed ROAA as the measure of bank profitability and controls for bank specific, industry

and macroeconomic variables. The bank specific variables include bank size (LnTA), Capital adequacy (ETA), Credit Risk (NPLsratio), Management/Operational Efficiency (CTIR) and Liquidity Risk (LTA). The industry variable include bank concentration (HHI-loan), and the macroeconomic variables consist of Inflation (CPI) and Economic Growth (GDPG).

### 5.3.1 Robust Fixed Effect Estimates

**Table 7: Robust Fixed Effect Estimates**

| | DEPENDENT VARIABLE | | |
|---|---|---|---|
| **PREDICTORS** | (1) ROAA | (2) ROAA | (3) ROAA |
| CID | 0.0137 | | |
| | (0.0586) | | |
| PCB | | 0.0208*** | |
| | | (0.00789) | |
| PCR | | | -0.0318 |
| | | | (0.0220) |
| lnTA | -0.229 | -0.240 | -0.159 |
| | (0.204) | (0.185) | (0.203) |
| ETA | 0.144*** | 0.144*** | 0.145*** |
| | (0.0456) | (0.0449) | (0.0430) |
| NPLsratio | -0.0589*** | -0.0590*** | -0.0584*** |
| | (0.0150) | (0.0149) | (0.0150) |
| CTIR | -0.0576*** | -0.0575*** | -0.0583*** |
| | (0.00810) | (0.00805) | (0.00775) |
| LTA | -0.00620 | -0.00554 | -0.00532 |
| | (0.00794) | (0.00773) | (0.00798) |
| HHI | -0.289 | -0.200 | -0.597 |
| | (1.255) | (1.178) | (1.317) |
| CPI | -0.00240 | -0.00300 | -0.00253 |
| | (0.00254) | (0.00234) | (0.00234) |
| GDPG | 0.0261 | 0.0249 | 0.0257 |
| | (0.0192) | (0.0187) | (0.0187) |
| Constant | 7.595*** | 7.533*** | 6.863** |
| | (2.871) | (2.651) | (2.867) |
| Observations | 1,627 | 1,627 | 1,627 |
| Number of id (banks) | 396 | 396 | 396 |
| R-squared | 0.397 | 0.399 | 0.402 |
| Prob >F | 0.0000 | 0.0000 | 0.0000 |

**Robust standard errors are in parentheses**

**Level of significance: *** p<0.01, ** p<0.05, * p<0.1 respectively**

***ROAA: Return on Average Asset (Bank Profitability), lnTA: natural log of Total Assets(bank Size), ETA: Equity to Total assets(Capital Adequacy), NPLsratio: Impaired loans to Gross Loans(credit risk), CTIR: Cost to Income Ratio(Management Efficiency), lTA: Loan to Total Asset(liquidity risk), HHI: Herfindhal - Hirshman Index(Loan-Bank Concentration), CPI: Consumer Price Index(Inflation), GDPG: Real Gross Domestic Growth rate, CID: Depth of Credit Information Index (Credit Information Sharing Scheme), PCB: Private Credit Bureau(Coverage), PCR: Public Credit Registry(Coverage)***

From Table 7 above, the results shown in column one (1) seeks to achieve the first objective of the study, whiles the results in column two (2) and three (3) provide response to the second objective of the study focusing on the main variables of study (CID, PCB and PCR). The results show that the bank specific variables which includes Capital adequacy (ETA), Credit Risk (NPLsratio) and Management/operation efficiency have significant impact on the profitability of banks within the Africa Region. These aforementioned explanatory variables report a 1% level of significance shown in columns 1, 2 and 3 respectively. Whereas Bank size (LnTA), Liquidity (LTA), bank concentration (HHI), Inflation (CPI) and Economic Growth (GDPG) do not show a significant impact on the profitability of banks within the Africa Region. Nevertheless, all the control variables (bank specific, industry and macroeconomic) yield expected signs in relation to theory and previous empirical studies.

The estimates for Capital Adequacy (ETA), measured by the ratio of equity to total assets shows a positive impact on profitability, and significant at 1% shown in columns 1, 2 and 3. This provides a strong indication that as equity increases, banks are able to significantly achieve a higher level of return on assets. This finding supports the signaling and bankruptcy cost hypothesis which is consistent with the findings of (Dietrich and Wanzenried, 2014,

Anthanasoglou et al., 2008). It implies that well capitalized banks within the African banking system will have a sound financial position. They can reduce the need for external funding, alleviate the cost of financial distress and will have the capacity to withstand losses.

The estimates for Non-performing loans ratio (NPLsratio), which measures credit risk show a negative and a statistically significant impact on bank profitability, at 1% level of significance with expected signs shown in columns 1, 2 and 3. This may imply that on the average banks within the African banking system fail to recognize impaired loans, and perhaps create reserves for writing – off these assets thereby reducing the return on assets. A desirable approach would be to improve credit transparency in the financial system. This could be harnessed through a well effective and efficient credit information sharing system to alleviate informational asymmetry, and associated negative impacts of adverse selection and moral hazard issues. This to a large extent can reduce the rate of defaults and improve bank lending, which in turn can increase profitability, all other things being equal.

The estimates for Management/Operational Efficiency (CTIR) is also negative, and statistically significant at 1% with expected signs in columns 1, 2 and 3. This is consistent with theory and other empirical studies (e.g. Francis, 2013), which explains that high cost of operation inversely affect bank profitability. Management/Operational efficiency indicator is an expense variable and describes how banks could be efficient in the utilization and allocation of human resources and technological improvement in banking. The negative impact of this variable on profitability could possibly be the high cost of operation across banks within the African region.

Bank size (LnTA) shows a negative but insignificant impact on bank profitability in columns 1, 2 and 3. Quite similar to the findings of Acaravci and Calim, 2013, it may suggest that larger banks tend to minimize the return on assets due to scale inefficiencies (diseconomies of scale). Liquidity (LTA), measured by the ratio of loans to total asset also show a negative rapport to bank profitability, and insignificant in columns 1, 2 and 3 respectively. This may suggest lower bank liquidity or illiquidity of banks within the sector, making banks more likely to sustain losses if a "fire-sale" of asset is required to meet liquidity needs ( see Berger et al., 2005).

Among the industry and macroeconomic predictors, namely HHI (bank concentration), CPI (inflation) and GDPG (economic growth) denotes an insignificant impact on profitability as shown in columns 1, 2 and 3 respectively. According to the suggestions provided by Nacear et al (2003), it follows that on the average banks in the African region do not make profits in inflationary periods or environment. Also Alexiou and Sofoklis (2009), are of the view that economic growth does not reflect any aspects of banking regulation and technological advancement in the banking sector, which is omitted from the regressions in the study. Hence could amount to these regression outcomes. The industry variable, which measures bank concentration (HHI) shows a negative but insignificant impact on the profitability of banks within the Africa Region, losing its explanatory power. This may imply that the more monopolistic the African banking system becomes, the lesser its capacity to convert its resources into profits. This may be the inefficiencies and deadweight losses attributable to monopolistic markets (Baye, 2010). On the contrary, a less concentrated banking system is able to utilize resources more efficiently to remain competitive.

### 5.3.2 Impact of the Depth of Credit Information (CID) on profitability of banks in Africa

In column 1 from table 7 above, the depth of credit information index (CID) show a direct relationship on banks' profitability. A unit increase in the depth of credit information sharing leads to a 0.0137 unit increase in the profitability of banks in the Africa Region. However, this show an insignificant impact on the profitability of banks. This finding provides a notable evidence from the Africa perspective converse to cross-country evidence (only 14 African countries out of 69 countries) in previous study (Houston et al., 2010), which explains that greater information sharing is universally positive and has significant impact on bank profitability.

This evidence from the Africa perspective, probably suggests that the rules/laws and practices surrounding the coverage, scope and accessibility of credit information sharing schemes renders it incomprehensive and ineffective to considerably improve bank performance (profitability). According to Jappelli and Pagano (2000), strict privacy protection laws, poor quality and type of data on credit histories gathered, and improper design of credit information scheme/system might render credit information sharing ineffective or inadequate in achieving desirable outcomes (e.g. improving bank profitability). Therefore, correcting adverse selection and moral hazard complications in the credit market might become problematic.

The findings further supports, confirms and clarify the arguments or opinions which some researchers /scholars (e.g. Honohan and Beck, 2007; Jappelli and Pagano, 2000; Luotos et al., 2007) held that Africa remains the region of the world with the least developed credit information scheme/system. Henceforth, on the average, the underdevelopment of the credit

information scheme within the region might probably be attributable to the insignificant impact of the depth of credit information sharing on bank profitability.

### 5.3.3 Impact of Private Credit Bureau (PCB) / Public Credit Registry (PCR) coverage on the profitability of banks

Notwithstanding the findings in section 5.3.2, the study disaggregate the information sharing scheme measure (CID) to consider whether it matters, if information sharing takes place through a private bureau or a public registry. The study uses Private Credit Bureau (PCB) coverage and Public Credit Registry (PCR) coverage as proxies (following Houston et al, 2010) to investigate their impact on bank profitability. According to Love and Mylenko (2003), information sharing through Private Credit Bureaus and Public Credit Registries should have different effect on credit market outcomes, since the two types of information sharing schemes differ significantly in the way they operate.

From Table 7 above, equation 2 presents the results for the impact of PCB coverage on bank profitability. Information sharing through Private Credit Bureau (PCB) show a positive and significant impact (at 1% level of significance) on bank profitability. A unit increase in information shared through private credit bureaus, significantly leads to a 0.0208 unit increase in the ROAAs with expected sign. The finding is consistent with the findings of Houston et al., 2010 implying that both positive and negative information that lenders share through Private Credit Bureaus improve bank profitability. The reason for PCB's being a robust predictor for bank profitability can be justified by the higher incidence of coverage/scope of borrowers' credit histories or past payments captured in the PCB's databases (Love and Mylenko, 2003; Miller,

2003). They provide much reliable and comprehensive information on payment/credit histories, which considerably mitigates associated adverse selection/moral hazard problems to allocate credits more efficiently, so that bank profits could be improved. Furthermore, the result prove that private information scheme are able to lower information asymmetries, support larger lending volumes and can reduce loan defaults, and thus increase bank profitability.

Equation 3 above, shows the impact Public Credit registry coverage on the profitability of banks in Africa. In spite of the positive impact previous studies (e.g. Houston et al, 2010) have shown, PCR's indicates a negative but insignificant impact on bank profitability with expected sign. A unit increase in the information shared through public credit registries, leads to 0.0318 unit decrease in the ROAA. Thus, unlike PCBs, credit information exchanges through public credit registries used as government antitrust policy mechanism is mandatory and compulsory (Jappelli and Pagano, 2000); Hence reduces banks' appropriation of informational rent and adds competitive pressure to the lending market. Since informational rent advantage confers to banks some market power over their clients/borrowers (Karapetyan and Stacesu, 2014), persistent information sharing through PCR's create competition, and in tend reduce their profitability (Pagano and Jappelli, 1993; Padilla and Pagano, 1997; Niemeyer, 2003) since interest rate decrement could be a commonly accepted reason.

### 5.4 Conclusion

The chapter discussed the results and findings using the fixed effect regression estimation after using the Hausman selection criteria and performing diagnostic tests (i.e. normality of variables, autocorrelation, heteroscedasticity and multicollinearity). The findings in the chapter shows that

the overall depth of credit information sharing in Africa over the 10 – year (2004 to 2013) of study is low and weak, and does not significantly support bank profitability. However, credit information exchanges through Private Credit Bureaus' (PCB) significantly matters to bank profitability in Africa. Also bank specific variables such as management/operation inefficiency, credit risk and capital adequacy were determined to impact bank profitability.

# CHAPTER SIX

# SUMMARY, CONCLUSIONS AND RECOMMENDATIONS

## 6.1 Introduction

The chapter presents the summary of the study underlining the objectives, and the results of the econometric analysis which provides answers to the research questions in Chapter one. Following the results and findings as outlined in Chapter Five, the study makes recommendations that will inform practice, policy and indicates some areas for future research.

## 6.2 Summary

Despite the fact that some scholars and researchers (e.g. Honohan & Beck 2007, Luotos et al., 2007) opinioned the African banking market to be underdeveloped; characterized with inadequate credit information, bank inefficiencies and macroeconomic downturn. The banking system in Africa is quickly realizing the need and the usefulness of credit information exchanges through Private Credit Bureaus and Public Credit Registries, as lenders (banks) and government agencies have strong demands for such financial infrastructure to reduce information asymmetry effects, to enhance competition and to make allocation of credits more profitable.

Based on the data sourced from the period 2004 to 2013 from the World Development Indicators on the Depth, and coverage of credit information sharing through Private Credit Bureaus and Public Credit Registries in Africa, the region seem to have a gradual paradigm shift from "physical collateral" to "reputational collateral". Alluding to the fact that the African banking

system is now reconsidering allocating credits more effectively and efficiently through credit information sharing schemes to improve performance and profits. Hence, the study seeks to provide some evidence and investigate whether the credit information sharing schemes within the Africa Region matters to bank profitability using an unbalanced financial data set of banks from the Bank Scope Database over a 10 – year (2004 to 2013) period. The study employed a static estimation technique using the fixed effect estimator (robust option), and used the traditional measure (ROAA) to proxy bank profitability, while controlling for bank specific, industry and macroeconomic variables to realize the set objectives of the research. The study proxy credit information sharing, both negative and positive information using the depth of credit information index following Houston et al., 2010 and Fosu, 2014. The index shows the extent of credit information sharing on a scale of 0 – 8 (based on the Doing Business Indicators, 2015), which measures the rules/laws and practices affecting the coverage, scope and accessibility of credit information available through Private Credit Bureaus and Public Registries. The study further disaggregate the credit information sharing schemes into Private Credit Bureaus coverage and Public Credit Registries coverage to examine its relative impact on the profitability of banks, as the two schemes are distinct in terms of purpose, ownership, status, coverage, ownership, data source and mode of accessibility.

The study found that the overall depth of credit information sharing in the Africa Region show an average of 1.67 (on a scale of 0 – 8) across 41 African countries. The regression results indicated a positive influence of the depth of credit information sharing on the profitability of banks, but an insignificant impact for that matter. This possibly suggest that the rules/laws, practice, design and the framework of the credit information schemes in Africa makes it

incomprehensive and ineffective to considerably support the profitability of banks (see Jappelli & Pagano, 2000). Interestingly, credit information sharing (both negative and positive information) through Private Credit Bureaus provides a positive and a significant impact on banks' profitability (at 1% significance level) with expected sign, while credit information exchanges through Public Credit Registry indicates a negative, but insignificant impact on the profitability of banks. Juxtaposing how credit information available through Private Credit Bureau matters to bank profitability. Moreover, from the statistical summary, credit information sharing through Private Credit Bureaus (coverage) on the average seem relatively higher than Public Credit Registries (coverage). The former indicated an average of 10.07% against the latter presenting an average of 3.46%. Furthermore, bank specific variables such as Capital Adequacy, credit risk and management/operational efficiency were also found to have high explanatory powers on the variability of the profitability of banks in Africa.

### 6.3 Limitation of Study

The quality of this study to a large extent depends on the consistency, reliability and accuracy of the data sourced from the Fitch IBCA's Bank Scope Database and the World Development Indicators over the period of study (2004 to 2013).

### 6.4 Conclusion

Unlike previous study by Houston et al., 2010 which provided a cross-country evidence (banks within 69 countries) on the impact of credit information sharing on bank profitability, this study is notable, as it is the first to investigate the impact of credit information sharing schemes on the profitability of banks in the Africa Region using the depth of credit information index and

Private Credit Bureau coverage and Public Credit Registry coverage as credit information sharing variables, from the World Bank World development indicators. The study provides evidence that credit information sharing within the banking system in the Africa Region is not universally positive, contrary to the findings of Houston et al., 2010, who based assertions on cross-country evidence (used only 14 African countries).

The results show that there is no empirical evidence to conclude that the depth of credit information sharing has a significant effect on the profitability of banks in Africa. And there is also no empirical evidence to conclude that Public Credit Registries have a significant impact on the profitability of banks in Africa. However, the study provide an empirical evidence to conclude that information exchanges or sharing through Private Credit Bureaus have a positive and significant effect on the profitability of banks in Africa.

## 6.5 Recommendations

### 6.5.1 Practice and Policy

The findings in the study suggest that credit information exchanges through Private Credit Bureaus supports banks profitability in the Africa Region. Therefore banks can however rely on the credit information (both negative and positive information) available through Private Credit Bureaus to reduce information asymmetric effects; reduce loan administration cost, increase lending volumes, allocate more credits to borrowers efficiently and improve overall profitability (Jappelli & Pagano, 1999). That notwithstanding, there is more room for improvement, since there is the need for persistent sharing of credit information and constant collaboration between banks and Private Credit Bureaus. This will help widen the coverage and scope of credit

information, and foster timely and accurate credit reports as borrowers become highly mobile and the degree of banking competition exacerbates. There is also the need for a more sophisticated communication technology such as more widespread level of internet access to lower the cost of information exchange (Luotos et al., 2007)

Also, to promote stability and competition in the banking system, the study recommends that governments can intervene by using the Creation of Public Credit Registries as antitrust devices. It may also provide competition for Private credit bureaus, forcing them to provide supplementary services not furnished by the Public Credit Registries, and to promote the standards of their information collection and dispersion to enhance the effectiveness of the credit information scheme. Furthermore, as suggested by Jappelli and Pagano (1999), the study also recommends that an effective Public Credit Registries should be introduced to compensate partly for the weak protection of creditors interest among African states to remedy the heighten moral hazard problems within the banking system.

The findings of the study again suggest that the overall depth of credit information sharing (measured as the rules/laws and practice affecting the coverage, scope and accessibility of credit information available through Private Credit Bureaus and Public Registries) does not support bank profitability as it show a positive but insignificant impact on profitability. As explained by Dell Villar et al, 2003 countries with strong legal and regulatory framework is able to be more successfully enforce information sharing rules, and deal appropriately with concerns over issues such as individual privacy. For that matter, since the banking system understudy in the African region is dominated by Public Credit Registries, governments within the Africa Region must take

the initiative to develop a comprehensive and a well effective credit information sharing scheme through formidable banking regulations to redefine the mode of operations, design and framework of the schemes to achieve desirable results. Also, parliament enact laws can be formulated to widen the scope, accessibility of credit information and coverage to include data on non - banking financial institutions ( e.g. insurance firms), utility companies, tax agencies and among others. As indicated in the study of Barth et al. (2009), this can make banks' predictive capacity more powerful, accurate and reliable to reducing information asymmetric effects and to allocate credits more profitably.

### 6.5.2 Future Research

The study sought to achieve its primary objective by examining the impact of credit information sharing schemes on banks' profitability in Africa using credit information sharing variables such as the depth of credit information index and the coverage of Private Credit Bureaus and Public Credit Registries following Houston et al., 2010. However, there are more avenues for future research to be carried out in this area, since the Africa Region has not been extensively studied in relation to Bank profitability and credit information sharing schemes.

Subsequent studies can proceed to examine this relationship among banks amid regional blocs and income brackets in the Africa Region, and make comparative performance analysis. The measure of Bank profitability can also be extended to include ROE, NIM and other non – traditional measures to ascertain how the results could vary across these measures. Moreover, future research can focus on other bank performance measures such as credit risk and liquidity to further realize the impacts of credit information sharing schemes. Above all, we recommend that

future research should provide country specific evidence on the impact of credit information scheme and bank performance by employing dynamic estimation techniques on either times series or panel studies.

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# APPENDICES

# APPENDIX 1

**Shapiro -Wilk W test for normality of data**

| variable | Obs | W | V | z | Prob>z |
|---|---|---|---|---|---|
| | | | | | |
| ROAA | 3633 | 0.280 | 1465.753 | 18.934 | 0.00000 |
| CID | 4041 | 0.962 | 84.19 | 11.554 | 0.00000 |
| PCR | 4041 | 0.549 | 1009.519 | 18.028 | 0.00000 |
| PCB | 4041 | 0.738 | 587.964 | 16.619 | 0.00000 |
| lnTA | 4041 | 0.986 | 30.974 | 8.947 | 0.00000 |
| ETA | 4009 | 0.676 | 721.044 | 17.146 | 0.00000 |
| NPLsratio | 2129 | 0.717 | 355.666 | 14.976 | 0.00000 |
| CTIR | 3885 | 0.814 | 401.835 | 15.607 | 0.00000 |
| lTA | 3775 | 0.994 | 12.853 | 6.64 | 0.00000 |
| HHI | 4041 | 0.786 | 479.992 | 16.09 | 0.00000 |
| CPI | 3613 | 0.921 | 160.852 | 13.192 | 0.00000 |
| GDPG | 3689 | 0.863 | 281.905 | 14.659 | 0.00000 |

# APPENDIX 2

**(A)**

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
   F(  1,     234) =      0.018
         Prob > F =      0.8928
```

**(B)**

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
   F(  1,     234) =      0.017
         Prob > F =      0.8978
```

**(C)**

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
   F(  1,     234) =      0.024
         Prob > F =      0.8777
```

# APPENDIX 3

**(A)**

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of ROAA
chi2(1) = 389.54

Prob > chi2 = 0.0000

**(B)**

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of ROAA
chi2(1) = 392.80
Prob > chi2 = 0.0000

**(C)**

Breusch-Pagan / Cook-Weisberg test for heteroskedasticity
Ho: Constant variance
Variables: fitted values of ROAA
chi2(1) = 448.59
Prob > chi2 = 0.0000

# APPENDIX 4

**(A)**

Fixed-effects (within) regression — Number of obs = 1627
Group variable: id — Number of groups = 396

R-sq: within = 0.3965 — Obs per group: min = 1
between = 0.3309 — avg = 4.1
overall = 0.2988 — max = 9

F(9,1222) = 89.22
corr(u_i, Xb) = -0.3454 — Prob > F = 0.0000

| ROAA | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| CID | .013706 | .0406763 | 0.34 | 0.736 | -.0660971 | .0935091 |
| lnTA | -.228542 | .1257567 | -1.82 | 0.069 | -.4752651 | .0181811 |
| ETA | .144303 | .0101801 | 14.18 | 0.000 | .1243306 | .1642755 |
| NPLsratio | -.0589409 | .0068319 | -8.63 | 0.000 | -.0723445 | -.0455373 |
| CTIR | -.0575662 | .0028254 | -20.37 | 0.000 | -.0631093 | -.0520231 |
| LTA | -.62037 | .5198299 | -1.19 | 0.233 | -1.640228 | .399488 |
| HHI | -.2888486 | .6007608 | -0.48 | 0.631 | -1.467485 | .8897882 |
| CPI | -.0024 | .001855 | -1.29 | 0.196 | -.0060394 | .0012394 |
| GDPG | .0260623 | .0131424 | 1.98 | 0.048 | .0002782 | .0518465 |
| _cons | 7.594864 | 1.63927 | 4.63 | 0.000 | 4.378768 | 10.81096 |
| sigma_u | 2.562769 | | | | | |
| sigma_e | 1.3573151 | | | | | |
| rho | .78094118 | (fraction of variance due to u_i) | | | | |

F test that all u_i=0: F(395, 1222) = 6.19 — Prob > F = 0.0000

**(B)**

```
Fixed-effects (within) regression               Number of obs      =      1627
Group variable: id                              Number of groups   =       396

R-sq:  within  = 0.3985                         Obs per group: min =         1
       between = 0.3206                                        avg =       4.1
       overall = 0.2913                                        max =         9

                                                F(9,1222)          =     89.96
corr(u_i, Xb)  = -0.3732                        Prob > F           =    0.0000
```

| ROAA | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| PCB | .0208201 | .0102319 | 2.03 | 0.042 | .0007461 | .0408942 |
| lnTA | -.2397819 | .1229035 | -1.95 | 0.051 | -.4809071 | .0013433 |
| ETA | .1443552 | .0101524 | 14.22 | 0.000 | .1244372 | .1642732 |
| NPLsratio | -.0589955 | .0068204 | -8.65 | 0.000 | -.0723764 | -.0456145 |
| CTIR | -.0574843 | .0028206 | -20.38 | 0.000 | -.0630181 | -.0519506 |
| LTA | -.554062 | .5181632 | -1.07 | 0.285 | -1.57065 | .4625261 |
| HHI | -.2002154 | .5983477 | -0.33 | 0.738 | -1.374118 | .9736873 |
| CPI | -.0029989 | .0018595 | -1.61 | 0.107 | -.0066471 | .0006494 |
| GDPG | .0249127 | .013119 | 1.90 | 0.058 | -.0008255 | .050651 |
| _cons | 7.53254 | 1.613893 | 4.67 | 0.000 | 4.366232 | 10.69885 |
| sigma_u | 2.6011867 | | | | | |
| sigma_e | 1.3550844 | | | | | |
| rho | .78654234 | (fraction of variance due to u_i) | | | | |

```
F test that all u_i=0:     F(395, 1222) =     6.15                 Prob > F = 0.0000
```

**(C)**

```
Fixed-effects (within) regression               Number of obs      =      1627
Group variable: id                              Number of groups   =       396

R-sq:  within  = 0.4020                         Obs per group: min =         1
       between = 0.3382                                        avg =       4.1
       overall = 0.3128                                        max =         9

                                                F(9,1222)          =     91.28
corr(u_i, Xb)  = -0.3431                        Prob > F           =    0.0000
```

| ROAA | Coef. | Std. Err. | t | P>\|t\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| PCR | -.0317635 | .0094529 | -3.36 | 0.001 | -.0503093 | -.0132178 |
| lnTA | -.1585444 | .1234612 | -1.28 | 0.199 | -.4007638 | .0836749 |
| ETA | .1447445 | .0101231 | 14.30 | 0.000 | .1248839 | .1646051 |
| NPLsratio | -.0584406 | .0068019 | -8.59 | 0.000 | -.0717853 | -.0450958 |
| CTIR | -.0583448 | .0028211 | -20.68 | 0.000 | -.0638795 | -.0528101 |
| LTA | -.5323183 | .5164834 | -1.03 | 0.303 | -1.545611 | .4809742 |
| HHI | -.5972114 | .6001186 | -1.00 | 0.320 | -1.774588 | .5801655 |
| CPI | -.0025332 | .0018359 | -1.38 | 0.168 | -.006135 | .0010686 |
| GDPG | .0257228 | .0130723 | 1.97 | 0.049 | .0000762 | .0513695 |
| _cons | 6.863204 | 1.620372 | 4.24 | 0.000 | 3.684184 | 10.04222 |
| sigma_u | 2.5532106 | | | | | |
| sigma_e | 1.3511504 | | | | | |
| rho | .78122005 | (fraction of variance due to u_i) | | | | |

```
F test that all u_i=0:     F(395, 1222) =     6.12                 Prob > F = 0.0000
```

# APPENDIX 5

**(A)**

Random-effects GLS regression — Number of obs = 1627
Group variable: id — Number of groups = 396

R-sq: within = 0.3809 — Obs per group: min = 1
between = 0.4334 — avg = 4.1
overall = 0.3885 — max = 9

Wald chi2(9) = 1040.66
corr(u_i, X) = 0 (assumed) — Prob > chi2 = 0.0000

| ROAA | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| CID | -.0160998 | .0332163 | -0.48 | 0.628 | -.0812025 | .0490029 |
| lnTA | -.1594999 | .0592407 | -2.69 | 0.007 | -.2756095 | -.0433903 |
| ETA | .0924275 | .007313 | 12.64 | 0.000 | .0780942 | .1067608 |
| NPLsratio | -.053254 | .0059823 | -8.90 | 0.000 | -.064979 | -.041529 |
| CTIR | -.0626069 | .0023169 | -27.02 | 0.000 | -.067148 | -.0580657 |
| LTA | -.9483009 | .3981812 | -2.38 | 0.017 | -1.728722 | -.1678799 |
| HHI | -.2183877 | .5279782 | -0.41 | 0.679 | -1.253206 | .8164306 |
| CPI | -.0017742 | .0015046 | -1.18 | 0.238 | -.0047232 | .0011748 |
| GDPG | .0239673 | .0124176 | 1.93 | 0.054 | -.0003707 | .0483053 |
| _cons | 7.743964 | .8979263 | 8.62 | 0.000 | 5.984061 | 9.503867 |
| sigma_u | 2.0460273 | | | | | |
| sigma_e | 1.3573151 | | | | | |
| rho | .6944025 | (fraction of variance due to u_i) | | | | |

**(B)**

Random-effects GLS regression — Number of obs = 1627
Group variable: id — Number of groups = 396

R-sq: within = 0.3814 — Obs per group: min = 1
between = 0.4326 — avg = 4.1
overall = 0.3895 — max = 9

Wald chi2(9) = 1041.48
corr(u_i, X) = 0 (assumed) — Prob > chi2 = 0.0000

| ROAA | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| PCB | .0047369 | .0053511 | 0.89 | 0.376 | -.0057511 | .0152249 |
| lnTA | -.181106 | .0591519 | -3.06 | 0.002 | -.2970416 | -.0651704 |
| ETA | .0915357 | .0073306 | 12.49 | 0.000 | .0771679 | .1059035 |
| NPLsratio | -.0533354 | .0059796 | -8.92 | 0.000 | -.0650552 | -.0416156 |
| CTIR | -.0626345 | .0023172 | -27.03 | 0.000 | -.0671761 | -.0580928 |
| LTA | -1.013501 | .3961942 | -2.56 | 0.011 | -1.790028 | -.2369749 |
| HHI | -.1162675 | .525922 | -0.22 | 0.825 | -1.147056 | .9145207 |
| CPI | -.0016761 | .0014988 | -1.12 | 0.263 | -.0046137 | .0012614 |
| GDPG | .0254046 | .0123719 | 2.05 | 0.040 | .0011561 | .049653 |
| _cons | 7.954721 | .8998485 | 8.84 | 0.000 | 6.19105 | 9.718391 |
| sigma_u | 2.0470679 | | | | | |
| sigma_e | 1.3550844 | | | | | |
| rho | .69531563 | (fraction of variance due to u_i) | | | | |

**(C)**

Random-effects GLS regression — Number of obs = 1627
Group variable: id — Number of groups = 396

R-sq: within = 0.3865 — Obs per group: min = 1
between = 0.4337 — avg = 4.1
overall = 0.3974 — max = 9

Wald chi2(9) = 1059.30
corr(u_i, X) = 0 (assumed) — Prob > chi2 = 0.0000

| ROAA | Coef. | Std. Err. | z | P>\|z\| | [95% Conf. | Interval] |
|---|---|---|---|---|---|---|
| PCR | -.0262454 | .0076725 | -3.42 | 0.001 | -.0412833 | -.0112076 |
| lnTA | -.1618627 | .0569436 | -2.84 | 0.004 | -.2734701 | -.0502554 |
| ETA | .0913226 | .0072756 | 12.55 | 0.000 | .0770628 | .1055824 |
| NPLsratio | -.0534468 | .0059598 | -8.97 | 0.000 | -.0651278 | -.0417658 |
| CTIR | -.0630299 | .0023132 | -27.25 | 0.000 | -.0675637 | -.0584961 |
| LTA | -.8531 | .3943842 | -2.16 | 0.031 | -1.626079 | -.0801212 |
| HHI | -.3056434 | .5209203 | -0.59 | 0.557 | -1.326628 | .7153416 |
| CPI | -.0015383 | .001494 | -1.03 | 0.303 | -.0044665 | .0013898 |
| GDPG | .0227509 | .0123078 | 1.85 | 0.065 | -.001372 | .0468738 |
| _cons | 7.819391 | .8834101 | 8.85 | 0.000 | 6.087939 | 9.550843 |
| sigma_u | 2.0470314 | | | | | |
| sigma_e | 1.3511504 | | | | | |
| rho | .69653854 | (fraction of variance due to u_i) | | | | |

# APPENDIX 6

**(A)**

| | ---- Coefficients ---- | | | |
|---|---|---|---|---|
| | (b) | (B) | (b-B) | sqrt(diag(V_b-V_B)) |
| | cidf | cidre | Difference | S.E. |
| | | | | |
| CID | 0.013706 | -0.0160998 | 0.0298058 | 0.0240655 |
| lnTA | -0.228542 | -0.1594999 | -0.0690421 | 0.1121253 |
| ETA | 0.144303 | 0.0924275 | 0.0518755 | 0.0072043 |
| NPLsratio | -0.0589409 | -0.053254 | -0.0056869 | 0.0034169 |
| CTIR | -0.0575662 | -0.0626069 | 0.0050407 | 0.0016581 |
| lTA | -0.0062037 | -0.009483 | 0.0032793 | 0.0034093 |
| HHI | -0.2888486 | -0.2183877 | -0.070461 | 0.2970536 |
| CPI | -0.0024 | -0.0017742 | -0.0006258 | 0.0011115 |
| GDPG | 0.0260623 | 0.0239673 | 0.002095 | 0.0046304 |
| | | | | |
| | b = consistent under Ho and Ha; obtained from xtreg | | | |
| | B = inconsistent under Ha, efficient under Ho; obtained from xtreg | | | |
| | | | | |
| | Test: Ho: difference in coefficients not systematic | | | |
| | | | | |
| | chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B) | | | |
| | = 69.07 | | | |
| | Prob>chi2 = 0.0000 | | | |

**(B)**

| | ---- Coefficients ---- | | | |
|---|---|---|---|---|
| | (b) | (B) | (b-B) | sqrt(diag(V_b-V_B)) |
| | pcrbf | pcrbre | Difference | S.E. |
| | | | | |
| PCB | 0.0208201 | 0.0047369 | 0.0160832 | 0.0088347 |
| lnTA | -0.2397819 | -0.181106 | -0.058676 | 0.1090598 |
| ETA | 0.1443552 | 0.0915357 | 0.0528195 | 0.0071621 |
| NPLsratio | -0.0589955 | -0.0533354 | -0.0056601 | 0.0034129 |
| CTIR | - | -0.0626345 | 0.0051502 | 0.0016547 |

| | | | | |
|---|---|---|---|---|
| | 0.0574843 | | | |
| lTA | -0.0055406 | -0.010135 | 0.0045944 | 0.0034152 |
| HHI | -0.2002154 | -0.1162675 | -0.0839479 | 0.2970613 |
| CPI | -0.0029989 | -0.0016761 | -0.0013227 | 0.0011302 |
| GDPG | 0.0249127 | 0.0254046 | -0.0004918 | 0.0047247 |
| | | | | |
| b = consistent under Ho and Ha; obtained from xtreg | | | | |
| B = inconsistent under Ha, efficient under Ho; obtained from xtreg | | | | |
| | | | | |
| | Test: Ho: difference in coefficients not systematic | | | |
| | | | | |
| | chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B) | | | |
| | = 72.76 | | | |
| | Prob>chi2 = 0.0000 | | | |

**(C)**

| | ---- Coefficients ---- | | | |
|---|---|---|---|---|
| | (b) | (B) | (b-B) | sqrt(diag(V_b-V_B)) |
| | pcrrf | pcrrre | Difference | S.E. |
| | | | | |
| PCR | -0.0317635 | -0.0262454 | -0.0055181 | 0.0056578 |
| lnTA | -0.1585444 | -0.1618627 | 0.0033183 | 0.1107223 |
| ETA | 0.1447445 | 0.0913226 | 0.0534219 | 0.0071615 |
| NPLsratio | -0.0584406 | -0.0534468 | -0.0049938 | 0.0033962 |
| CTIR | -0.0583448 | -0.0630299 | 0.0046851 | 0.0016562 |
| lTA | -0.0053232 | -0.008531 | 0.0032078 | 0.0034023 |
| HHI | -0.5972114 | -0.3056434 | -0.291568 | 0.3080777 |
| CPI | -0.0025332 | -0.0015383 | -0.0009949 | 0.0010935 |
| GDPG | 0.0257228 | 0.0227509 | 0.0029719 | 0.0047234 |
| | | | | |
| | b = consistent under Ho and Ha; obtained from xtreg | | | |
| | B = inconsistent under Ha, efficient under Ho; obtained from xtreg | | | |
| | | | | |
| | Test: Ho: difference in coefficients not systematic | | | |
| | | chi2(9) = (b-B)'[(V_b-V_B)^(-1)](b-B) | | |
| | | = 69.69 | | |
| | | Prob>chi2 = 0.0000 | | |

# APPENDIX 7

**(A)**

| Variable | VIF | 1/VIF |
|---|---|---|
| | | |
| lnTA | 1.53 | 0.655279 |
| CID | 1.53 | 0.655721 |
| HHI | 1.24 | 0.807922 |
| lTA | 1.17 | 0.855418 |
| ETA | 1.14 | 0.873505 |
| CPI | 1.14 | 0.875945 |
| GDPG | 1.14 | 0.879113 |
| CTIR | 1.14 | 0.880115 |
| NPLsratio | 1.06 | 0.939768 |
| | | |
| Mean VIF | 1.23 | |

**(B)**

| Variable | VIF | 1/VIF |
|---|---|---|
| lnTA | 1.48 | 0.674258 |
| PCB | 1.4 | 0.715401 |
| HHI | 1.23 | 0.814585 |
| ETA | 1.16 | 0.860009 |
| lTA | 1.15 | 0.870897 |
| CTIR | 1.15 | 0.87277 |
| CPI | 1.15 | 0.873333 |
| GDPG | 1.1 | 0.906152 |
| NPLsratio | 1.07 | 0.932108 |
| | | |
| Mean VIF | 1.21 | |

**(C)**

| Variable | VIF | 1/VIF |
|---|---|---|
| | | |
| lnTA | 1.28 | 0.780364 |
| HHI | 1.2 | 0.835772 |
| lTA | 1.15 | 0.870564 |
| CPI | 1.14 | 0.877638 |
| CTIR | 1.14 | 0.878792 |
| ETA | 1.13 | 0.88648 |
| GDPG | 1.08 | 0.927308 |
| NPLsratio | 1.06 | 0.94005 |
| PCR | 1.06 | 0.941573 |
| | | |
| Mean VIF | 1.14 | |

# APPENDIX 8

**List of 41 African Countries with Private Credit Bureau/Public Credit Registry Coverage**

| | | | | |
|---|---|---|---|---|
| Algeria | Chad | Kenya | Namibia | Togo |
| Angola | Congo | Liberia | Niger | Tunisia |
| Benin | Dem. Rep. Congo | Libya | Nigeria | Uganda |
| Botswana | Djibouti | Madagascar | Rwanda | Zambia |
| Burkina Faso | Egypt | Mali | Senegal | Zimbabwe |
| Burundi | Equatorial Guinea | Mauritania | Sierra Leone | |
| Cameroon | Ethopia | Mauritius | South Africa | |
| Cape Verde | Gabon | Morocco | Sudan | |
| Central Africa Republic | Ghana | Mozambique | Swaziland | |