

Credit Information Sharing Coverage and Depth and Their Impact on Bank Non-Performing Loans

Baah Aye Kusi
University of Ghana Business School,Department of Finance

Kwadjo Ansah-Adu, Mphil
Valley View University,Banking and Finance Department

Abstract
This study provides an international evidence of how credit information sharing coverage and depth impact on bank non-performing loans across the income brackets categorized by the World Bank. Employing anova and robust standard errors OLS estimation techniques, the results suggest that both coverage and depth of information shared are imperative in reducing bank non-performing loans. However, coverage of credit information shared is more effective in reducing non-performing loans with public credit registries while depth of information shared is more effective with private credit bureaus. The findings further prove that the use of both private and public bureaus and registries are more effective in reducing non-performing loans than using either of them. The study finally finds that non-performing in low income countries varied significantly from that of high income countries. These findings are largely consistent with previous studies and require the implementation of policies that deepen the coverage and depth of credit information shared across the income brackets especially low income countries.

1. Introduction
Information sharing through Credit Referencing Bureaus (CRBs) have become one of the credit risk management tools employed by banks in recent times especial on continent of Africa although information sharing have been in existence for a long time in some European and American countries. Credit Referencing Bureaus are private or public institutions that collect financial data, process the data, store it and at the request of lenders and other financial institutions, they (CRBs) share or provide the credit worthiness status or report for lending decision by the requesting institution. Empirical studies suggest that information sharing through CRBs are able to help reduce adverse selection (Pagano and Jappelli, 1993) and moral hazard (Padilla and Pagano, 2000) which in turn reduce non-performing loans (credit risk). Specifically on the effect of information sharing through CRBs on credit risk, studies argue that information sharing reduces credit risk exposure through the screening and incentive effects. For instance, Doblas-Madrid and Minetti (2013) found that information sharing through CRBs help improve delinquent loans. Again, Brown and Zehnder (2007) also find that CRBs can help improve loan repayment. Powell et al. (2004) also proves that CRBs are able to reduce default rates. Kallberg and Udell (2003), Brown et al. (2009) and Bennardo et al. (2007) have found similar results. These studies have focused on the impact of credit information sharing on bank non-performing loans at either country or sub-regional levels. However, none of these studies cited considered the impact of credit information sharing coverage and depth on bank non-performing loans at the global level. Hence, this study attempts to establish the impact of credit information sharing coverage and depth on non-performing loans at a globe level employing the five income brackets defined by the World Bank since the income brackets capture all countries in the world. Again, following the arguments of Miller (2003) and Triki and Gajigo (2012) that private credit bureaus are more effective that public credit registries, we examine this argument at the global level using private credit bureau and public credit registry coverage. The study further explore if the depth of information shared impacts non-perform loans. Again, the reacts credit depth of information shared with private bureau coverage and public registry coverage. The study also tests for significant difference (if any) in non-performing loans among the income brackets. We are motivated to test for difference in non-performing loans due to that arguments that high income countries (developed countries) have better financial regulations and institutions (see Miller, 2003; Dankov et al., 2007) than the low income countries (developing countries). From the above, it is evident that the impact of impact of credit information sharing coverage and depth on non-performing loans are important and long overdue. Hence, this study fills these gaps using the five income bracket groupings by the World Bank.

2. Literature Review
2.1 Theoretical Review: Information Asymmetry and Information Sharing
Earlier theoretical review suggests that credit risk in banks emanates from information asymmetry leading to adverse selection and moral hazard (see Freimer and Gordon, 1965; Stiglitz and Weiss, 1981; Freixas and Rochet, 1997). Information asymmetry can be viewed as the lack of complete information in the credit market from both the lenders and borrowers side ((Freixas and Rochet, 1997; Myerson, 1991; Aumann, 1987). In an

attempt to reduce the effect of information asymmetry which may lead to credit risk, Gehrig and Stenbacka (2007), Padilla and Pagano (1997), Padilla and Pagano, (2000), Pagano and Jappelli (1993) and Kallberg and Udell (2003) prove and suggest that information sharing in the credit market helps to reduce adverse selection and moral hazard. Information sharing in the credit market is done through either public or private credit referencing bureaus. These bureaus collect credit or financial data, process the data and report on the credit worthiness of individuals and corporate entities at the request of banks and other financial institutions. Though both private and public credit bureaus are perfect substitutes in theory, empirical evidence or studies suggest that private credit bureaus are more effective (see Miller, 2003; Singh et al., 2009).

2.2 Empirical Review

The impact of information sharing through credit referencing bureaus has received much attention in recent years especially in developing economies. Empirical studies suggest that information sharing have several impacts on banks especially credit risk. Studies that examine the impact of information sharing 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 suggest that information sharing enables banks evaluate and identify clients ability to service or repay their loans, hence enhance the default predictive power of banks and making them more robust to adverse selection (Pagano and Jappelli, 1993). Second, the incentive effect pose that bank clients are motivated to repay or service loans because of the fear of future denial of loan or credit by another lender because default with one lender is captured and shared by all lenders. Hence, bank clients are pressured to perform and settle their loans because of denial of credit in the future upon default (Padilla and Pagano, 2000). We highlight some key empirical studies on the effect of information sharing on credit risk.

Pagano and Jappelli (1993) 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. This leads to increased aggregate lending in the credit market. Also, Padilla and Pagano (2000) prove that Credit-sharing institutions can raise the borrowers' cost of defaulting loans or credit thereby increasing loan repayment by borrowers, hence moral hazard.

Jappelli and Pagano (2002) illustrated that credit information sharing through credit referencing bureaus increases bank lending and reduces default rates. Kallberg and Udell (2003) also point out that historical information collated by credit bureaus have powerful default predictive ability, hence making banks more resistant to adverse selection and in turn reducing bank credit risk.

Barron and Staten (2003) also provide evidence that lenders can significantly reduce default rates by sharing and involving more complete and in-depth borrower information in their predictive models. Also, Powell et al. (2004) employ banks in Brazil and Argentina and found similar results indicating that more information sharing leads to reduced default rates.

Berger and Frame (2006) demonstrated that information sharing increases quantity of small business loans and also extended credit to marginal borrowers on the US. Bennardo, Pagano and Piccolo (2007) show that over-indebtedness can be reduced through sharing of credit information among lenders and banks as individual borrowers classified as highly indebted receive less credit and ultimately reduce the over-indebtedness of borrowers.

Brown and Zehnder (2007) empirically established that the credit market would collapse in the absence of credit information sharing and reputational banking. Their study further suggested that information sharing encourages borrowers to honor their loans thereby allowing lenders to identify borrowers with good credit history. Doblas-Madrid and Minetti (2013) proved that credit information sharing borrowers improve their repayment performance as delinquent repayment decreased.

3. Methodology

In this study, the panel and anova techniques are employed. The anova technique is used to establish the difference in non-performing loans among income brackets. The null hypothesis affirms that difference in mean values of bank non-performing loans for all the income brackets are the same and equal to zero while the alternate hypothesis affirms that the difference in mean values of bank non-performing loans are all not the same and not equal to zero. The null and alternate hypotheses of the anova technique are mathematically stated as:

$$\mathbf{H_o: \mu_1 = \mu_2 = \mu_3 = \mu_4 = \mu_5 = 0}$$

$$\mathbf{H_a: \mu_1 \neq \mu_2 \neq \mu_3 \neq \mu_4 \neq \mu_5 \neq 0}$$

The study also takes advantage of the superior qualities of a panel data as suggest by Wooldridge (2008) and Brooks (2008) to examine how private credit bureaus coverage (PCBC), public credit resgistries coverage (PCRC) and depth of credit information shared (CII) impact on non-performing loans across the five income brackets from 2000 to 2013. The study again react PCBC and PCRC with CII to establish the impact of coverage, quality and availability credit information shared through private bureaus and public registries on bank non-performing loans. The study obtained income bracket variables from World Development Indicators (WDI). The general form of a panel data model is stated as $Y_{it}= \alpha_i + \gamma_t + \beta X_{it} + \varepsilon_{it}$ ……….**(1)**

Where: Subscript i indicates the cross sectional dimension (income bracket) i=1. . . *N* and t indicates the time series dimension (time), t=1…T; *Yit* is the dependent variable; α_i is scalar and constant term for all periods (t) and specific to an income bracket (*i*); γ_t is the time fixed effect; *β is a k*×1 vector of parameters to be estimated on the independent variables for the independent variables; *Xit is a 1*× k vector of observations on the independent variables comprising of independent variables in the model which includes controlled variables and *Eit* which is iid is the error term.

From an econometrics point of view, we estimate our regression models and expressed it as:

$$\mathbf{NPL_{it} = \beta_{0it} + \beta_1\ GDPG_{it} + \beta_2\ GDS_{it} + \beta_3\ IRS_{it} + \beta_4\ CPI_{it} + \varepsilon_{it}}\ldots\ldots\ \mathbf{(2)}$$
$$\mathbf{NPL_{it} = \beta_{0it} + \beta_1\ PCRC_{it} + \beta_2\ GDPG_{it} + \beta_3\ GDS_{it} + \beta_4\ IRS_{it} + \beta_5\ CPI_{it} + \varepsilon_{it}}\ldots\ldots\ \mathbf{(3)}$$
$$\mathbf{NPL_{it} = \beta_{0it} + \beta_1\ PCBC_{it} + \beta_2\ GDPG_{it} + \beta_3\ GDS_{it} + \beta_4\ IRS_{it} + \beta_5\ CPI_{it} + \varepsilon_{it}}\ldots\ldots\ \mathbf{(4)}$$
$$\mathbf{NPL_{it} = \beta_{0it} + \beta_1\ CII_{it} + \beta_2\ GDPG_{it} + \beta_3\ GDS_{it} + \beta_4\ IRS_{it} + \beta_5\ CPI_{it} + \varepsilon_{it}}\ldots\ldots\ \mathbf{(5)}$$
$$\mathbf{NPL_{it} = \beta_{0it} + \beta_1\ (PCRC_{it}\ x\ CII_{it}) + \beta_2\ GDPG_{it} + \beta_3\ GDS_{it} + \beta_4\ IRS_{it} + \beta_5\ CPI_{it} + \varepsilon_{it}}\ldots\ldots\ \mathbf{(6)}$$
$$\mathbf{NPL_{it} = \beta_{0it} + \beta_1\ (PCBC_{it}\ x\ CII_{it}) + \beta_2\ GDPG_{it} + \beta_3\ GDS_{it} + \beta_4\ IRS_{it} + \beta_5\ CPI_{it} + \varepsilon_{it}}\ldots\ldots\ \mathbf{(7)}$$

3.1 Variable Description and Selection

Non-Performing loans (NPL)

Following Lousiz (2012), Aver (2008) and Fofack (2005) non-performing loan is employed as a dependent variable in the is study. Non-performing loans is the aggregation or combination of all past defaulted loans in a given income bracket as a point in time. Non-performing loans are seen as undesirable outputs in the financial systems that needs to be minimized or at best eradicated (Fujii, Managi and Matousek, 2014). Non-performing loan is sourced from World Development Indictors (WDI) and measured as a ratio of non-performing loans to gross loans and advances.

Private Credit Bureaus coverage (PCBC), Public Credit Registries Coverage (PCRC) and Credit Information Sharing Depth (CII)

Three (3) different variables are used to proxy information sharing. Credit referencing bureau be it private or public is deemed to have a negative impact on non-performing (Behr and Sonnekalb, 2012; Berger and Frame, 2006; Kallberg and Udell, 2003; Barron & Staten, 2003; Powell et al., 2004). The study proxy private credit bureaus and public credit registries with private credit bureaus coverage and public credit registry coverage in the income brackets. However following Miller (2003) and Triki and Gajigo (2012), the study expects both proxies will have an inverse relationship with non-performing loans but with private bureaus being more effective. These variables are adapted from WDI and measured as the percentage of adults covered by the information sharing institution (whether private or public) to the total population. CII measures the rules affecting the deepness, accessibility and quality of credit information sharing through private and public credit referencing bureaus and registries. The index ranges from 0 to 6, with higher values indicating the deepened, availability and quality of credit information shared from public registries and a private bureaus, to facilitate lending decisions. The study expects that non-performing loans and CII to be negatively related.

Gross Domestic Product Growth (GDPG)

There appears to be empirical evidence of an inverse relationship between the growth in GDP and non-performing loans (see Salas and Suarina, 2002; Rajan and Dhal, 2003; Fofack, 2005; and Jimenez and Saurina, 2005). The justification presented by earlier empirical studies for this negative relationship is that strong positive growth in GDP often translates or converts into more income which boots up the debt servicing ability of borrower which in tend lowers non-performing loans. Gross domestic product growth is measured as the current year's gross domestic product minus the year's gross domestic product all divided by the previous year's gross domestic product.

Gross Domestic Savings (GDS)

Gross Domestic Savings measures the amount of money residence in an income bracket is able to save or keep out of their disposable income. Gross domestic savings is obtained from WDI and computed as a ratio of gross domestic savings to gross domestic product. Following the classical theory of economics, the study expects a positive impact of gross domestic savings on non-performing loans. That is, an increase in savings leads to increased availability of credit to advanced as loans and hence, a higher probability of increased non-performing loans.

Interest Rate Spread (IRS)

Interest rate spread is measured as the difference between the lending rate and deposit rate of a country. Interest rate spread is viewed as cost to access to credit. That is, since interest rate spread is seen as a cost to access to finance, an increase in lending rate will lead to an increase in interest rate spread and hence, reduces the ability or willingness of borrowers to honour loan servicing adequately and promptly (Jiménez and Saurina, 2005; Aver, 2008) and hence increasing non-performing loans. The study anticipates a positive impact of interest rate spread on non-performing loans. The interest rate variable id obtained from WDI.

Consumer Price Index (CPI)

The study uses consumer price index as an inflation variable sourced from WDI. Literature provides proof of a positive relationship between the inflation rate and non-performing (see Louzis 2012; Chaibi and Ftiti 2015; Fofack, 2005). These studies argue that as inflation soars up, it reduces the ability of borrowers to honor their loan repayment leading to increased default. However following classical theory of economic, this study expects a negative relation between non-performing loans and inflation. This is because; classical theory of economics suggests that inflation reduces the monetary value or purchasing power of currencies implying that the monetary value of accumulated non-performing loans will reduce; hence a negative relationship.

Table 1: Summary of Variables

Variables	Smybol	Source of Data	Expected Sign	Description	Measurement of Variables
Non-Performing Loans	npl	World Development Indicators		Dependent Variable	Non-Performing Loans divided by gross loans and advances
Public Credit Registry Coverage	pcrc	World Development Indicators	-	Independent Variable	Adult population covered by Public Credit Registries divided by total population
Private Credit Bureaus Coverage	pcbc	World Development Indicators	-	Independent Variable	Adult population covered by Private Credit Bureaus divided by total population
Credit Information Sharing Depth	lncii	World Development Indicators	-	Independent Variable	As measured by World Development Indictors
Gross Domestic Product Growth	gpdg	World Development Indicators	-	Independent Variable	Current year GDP minus previous year GDP divided by previous year GDP
Gross Domestic Saving	gds	World Development Indicators	+	Independent Variable	Gross Domestic Saving divided by Gross domestic product
Interest Rate Spread	lnirs	World Development Indicators	+	Independent Variable	Log of Lending rate minus deposit rate
Consumer Price Index	cpi	World Development Indicators	-	Independent Variable	As measured by World Development Indictors

4. Empirical Results

Table 2 below shows the descriptive statistics on the variables employed in the robust standard errors Ordinary Least Squares estimation technique used for this study. The descriptive statistics table covers periods between 2000 and 2013. The table shows the mean, standard deviation, minimum, maximum, normatity (SWilk) and the acceptability (VIF) of each variable. From the minimum and maximum values of each variable, it is evident that none of the values is an outlier. Brook (2008) state that outliers distort the precision of regression estimates; hence leading to inconsistent, inefficient and biased coefficient estimates. From this, the study eliminates the effect of outliers. The standard deviation as reports mild variation within the variables indicating evidence of preciseness of model estimates. From the Shaprio Wilk normality test (SWilk), all (except for interest rate spread) the variables are significant and normality distributed around their means implying that the variables are linear and hence a linear regression can be used to estimate these variables. Wooldridge (2008) states that it is imperative to test for normality in order to choose either normal or non-normal distribution estimation form for coefficient estimates to be BLUE.

Table 2: Descriptive Statistics

Variables	Obs.	Mean	Std. Dev.	Min	Max	Swilk	VIF
npl	46	0.0519	0.0348	0.0130	0.1720	0.0000***	-
pcrc	70	0.0433	0.0456	0.0000	0.1612	0.0000***	1.72
pcbc	70	0.1285	0.1597	0.0000	0.5288	0.0000***	1.77
lncii	50	0.9075	0.5119	-0.2136	1.4458	0.0000***	2.24
gpdg	70	0.0493	0.0225	-0.0355	0.0865	0.0138**	1.73
gds	68	0.2363	0.0777	0.0886	0.3443	0.0000***	1.72
cpi	70	0.0497	0.0208	0.0120	0.1106	0.0026***	1.35
lnirs	56	0.0781	0.0232	0.0388	0.1352	0.1476	2.33

Significance Level: (*)< 10%, (**)< 5%, (***)< 1%

Table 3 below presents the Pearson's correlation matrix which serves as a means for screening for high collinearity between pairs of the independent variables. Following Kennedy (2008), the study set a threshold of 0.7 for the Pearson's correlation to be considered as multicollinear. Hence, the study finds evidence of multicollinearity between logged values of credit information sharing depth and interest rate spread. However, the two variables are kept in the OLS model because, Variance Inflation Factor (VIF) in Table 2 suggest that both variables are acceptable in the model and can be used since their VIF values do not exceed the threshold of 10 (Brook, 2009; Kennedy, 2008).

Table 3: Pearson's Correlation Matrix

	npl	pcrc	pcbc	lncii	gpdg	gds	cpi	lnirs
npl	1							
pcrc	-0.5476***	1						
pcbc	-0.5293***	0.7796***	1					
lncii	-0.5637***	0.7944***	0.8032***	1				
gpdg	-0.0086	-0.1126	-0.4122***	-0.4464***	1			
gds	-0.1078	0.5000***	0.2497**	0.657***	0.2544**	1		
cpi	0.1127	-0.2195*	-0.4512***	-0.5565***	0.4949***	-0.1148	1	
lnirs	0.6677***	-0.4547***	-0.6567***	-0.8400***	0.1646	-0.5677***	0.4229***	1

Significance Level: (*)< 10%, (**)< 5%, (***)< 1%

Table 4a below reports the anova results of the difference in bank non-performing loans across the income bracket groups as per the World Bank classification. With a null hypothesis of no significant difference in access to bank credit to private sector across the five income bracket groupings, the anova results repots an F-critical of 2.8270 and a p-value of 0.0650 indicating that the study rejects the null hypothesis of no significant difference in bank non-performing loans across the income bracket groupings and concludes that there is a significant difference (under 10%) in bank non-performing loans across the income bracket groupings.

4.1 ANOVA Results

Table 4a: Difference in Bank Non-performing loans across the Income Brackets

ANOVA

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	0.0087	3	0.0029	2.6587	0.0605*	2.8270
Within Groups	0.0459	42	0.0011			
Total	**0.0546**	**45**				

Significance Level: (*)< 10%, (**)< 5%, (***)< 1%

Further analysis of the anova technique shown in Table 4b below reveals that Low Income Countries' bracket is the only income bracket group that is significantly different from the other income brackets. Significant under 1%, a unit increase in Low income countries will results in 0.038 unit increase in non-performing loans across all the income brackets. This finding provides evidence in support of result earlier empirical studies that argue that high income countries (developed countries) have strong credit regulations and institutions which make the financial system more effective and efficient in dealing undesirable (see Miller, 2003, Ahmad and Ariff, 2007).

Table 4b: Difference in Bank Non-performing loans between the Income Brackets

NPL	**Coef.**	**T-Stats**
High Income Countries	-	-
Upper Middle Income Countries	0.024	1.79
Middle Income Countries	0.027	1.92
Low Middle Countries	0.038	2.71***
R-Squared	**0.16**	
No. of Obs.	**45**	

Significance Level: (*)< 10%, (**)< 5%, (***)< 1%

4.2 OLS Robust Standard Errors Regression Results

Table 5 below reports the OLS robust standard errors regression outputs of six different non-performing loans models. Model 1is the baseline model and estimated using no credit information sharing variable while Models 2 and 3 are estimated using public credit registries coverage (pcrc) and private credit bureaus coverage (pcbc) respectively. In model 4, credit information sharing depth (representing accessibility, quality and span of information sharing) of both private bureaus and public registries (lncii) is employed to estimate the non-performing loans model while in models 5 and 6 public credit registries coverage (pcrc) and private credit bureaus coverage (pcbc) are reacted with credit information sharing depth (lncii) respectively.

Table 5: Impact of Credit information Sharing Coverage and Depth on Bank Non-Performing Loans

	NPL Model 1	**NPL Model 2**	**NPL Model 3**	**NPL Model 4**	**NPL Model 5**	**NPL Model 6**
pcrc		-0.303 (3.95)***				
pcbc			-0.068 (1.16)			
lncii				-0.033 (3.65)***		
pcrc X lncii					-0.093 (2.57)**	
pcbc X lncii						-0.076 (3.29)***
gpdg	-0.816 **(4.22)*****	-0.771 **(4.58)*****	-0.754 **(4.28)*****	-0.350 **(5.30)*****	-0.345 **(3.57)*****	-0.275 **(3.42)*****
gds	0.126 **(1.16)**	0.290 **(2.69)****	0.178 **(1.29)**	0.157 **(6.90)*****	0.177 **(3.87)*****	0.084 **(2.24)****
cpi	-0.631 **(3.13)*****	-0.560 **(3.23)*****	-0.588 **(2.93)*****	-0.198 **(4.58)*****	-0.185 **(2.69)*****	-0.166 **(2.67)****
lnirs	0.156 **(6.38)*****	0.142 **(5.40)*****	0.141 **(4.60)*****	0.038 **(8.04)*****	0.053 **(5.38)*****	0.007 **(0.42)**
cons	0.518 **(6.27)*****	0.442 **(4.89)*****	0.463 **(4.35)*****	0.166 **(14.38)*****	0.168 **(6.35)****	0.074 **(1.91)**
R-Square	0.7	0.78	0.72	0.79	0.69	0.73
Obs.	36	36	36	23	23	23
Prob>F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Significance Level: (*)< 10%, (**)< 5%, (***)< 1%

From Table 5 above, the baseline model (Model 1) is estimated excluding information sharing variables. Model 1 is able to explain 70% of the total variations in non-performing loans across the income brackets without the inclusion of information sharing variables. It further reports that gross domestic product growth rate and inflation rate are negatively related to bank non-performing loans while gross domestic savings and inflation are positively related to bank non-performing loans. However, gross domestic product growth rate, inflation and interest rate spread were the only significant variables.

In models 2 and 3, the study employs public credit registry coverage and private credit bureau coverage respectively to establish the impact of information sharing on bank non-performing loans. Significant under 1%, public credit registry coverage reduces bank non-performing loans by 30.3% in model 2 while private credit bureau coverage reduces bank non-performing loans by 6.8% but insignificant in model 3. Gross domestic product growth rate, inflation and interest rate spreads are consistently significant under 1% in models 2 and 3 while gross domestic savings is only significant under 5% in model 2. Model 2 is able to explain 78% of the total variations in bank non-performing loans while model 3 explains 72% of that same variation. This finding implies that public credit registries are more effective in reducing and explaining the variations in bank non-performing loans than private credit bureau in terms of coverage. This contradicts the finding of Miller (2003).

From Table 5, Model 4 (preferred model) reports the impact of private bureaus and public registry credit information sharing depth on bank non-performing loans. The Model reports that a 100% increase in depth of information shared by both private bureaus and public registries results in 3.3% reduction in bank non-performing loans across the income brackets and is significant under 1%. Again gross domestic product growth rate and inflation rate are significantly and negatively related to bank non-performing loans while gross domestic savings and inflation are positively and significantly related to bank non-performing loans. this finding is in line with Kallberg and Udell (2003) and Barron and Staten (2003) who argue that the inclusion of more in-depth or detailed data make banks robust to adverse selection and moral hazard and hence reduced bank non-performing loans. Model 4 is the preferred model and is able to explain 79% (highest compared to the other five models) of the total variation in non-performing loans across the income brackets.

In models 5 and 6, the study interacts depth of credit information shared with public credit registry coverage and private credit bureau coverage respectively to establish the impact of information sharing on bank non-performing loans. Significant under 5% and 1% in models 5 and 6 respectively, the interaction between depths of information shared with public credit registry coverage and private credit bureau coverage reduces bank non-performing loans by 9.3% and 7.6% in models 5 and 6 respectively across the income brackets. Gross domestic product growth rate, gross domestic savings and inflation are consistently significant in models 5 and 6. Additional in model 5, interest rate spread is significant under 1%. Model 5 is able to explain 69% of the total variations in bank non-performing loans while model 6 explains 73% of that same variation. This finding implies increasing the coverage and depth of information shared by private credit bureau and public credit registries reduces bank non-performing loans. However, private bureaus are more effective in reducing bank non-performing loans. This findings supports that assert of Miller (2003) that private bureaus are more effective due to their ability to collect or gather more detailed credit data or information.

5. Robustness Checks and Diagnostics

To ensure our OLS model produces the best linear, unbiased and efficient coefficients, the study checks for outliers, multicollinearity, normality of variables, heteroskedasticity and autocorrelation. The study screened for outlier and found no outlier using the descriptive statistics. The pearson's correlation and Variance Inflation Factor (VIF) were employed to check for multicollineraity.

To ensure normality of variables (which is a key assumptions in regression), the study used the Shaprio Wilk normality test which provided evidence of normality (under 1%) for all variables except for interest rate spread. Employing the Breusch-Pagan / Cook-Weisberg test for heteroskedasticity and Wooldridge test for autocorrelation, the study found evidence of non-constant variance and autocorrelated residuals in the models. Hence, the study employed the robust standard error option to correct for heteroskedasticity and autocorrelation in Stata 13. From the robust standard errors OLS regression outputs in Table 5, all the variable together are jointly significant (as indicated by Prob> F = 0.0000) and are able to explain the total variation in bank non-performing loans across the five income bracket groupings by the World Bank. Again with a total number of 70 observations (five (5) income brackets multiplied by 14 years of data (2000 to 2013)), models 1 to 3 captures 51.43% of total observations while models 4 to 6 captures 37.14% of the total observations. Hence, the study exceeds the econometrics threshold of 30% for all the six (6) models. These are indications that the models are fit and can be used for generalization to a large extent.

6. Conclusions and Policy Implications

Information sharing is argued to have several benefits to the credit market and hence has attracted much attention from both corporate and academic researchers at country and sub-regional levels. In this study, the paper investigate the impact of information sharing coverage and depth (for both private and public credit referencing) on bank non-performing loans across the five income brackets. The study is able to provide a number of international evidences. First, the study establish that non-performance loans in low income countries vary significantly from the higher income bracket countries inducing the argument that higher income countries have better financial regulations and institutions that are robust to undesirable outputs in their financial systems (see Miller, 2003; Ahmad and Ariff, 2007; Brown et al., 2009). Second, the study establishes that in terms of coverage, public credit registries are more effective compared to private credit bureaus in reducing bank nonperforming loans which contradicts the finding of Miller (2003). However interacting coverage and depth of information shared, private bureaus became more effective in reducing bank non-performing loans than public credit registries which is consistent with Miller (2003). This third finding implies that, both coverage and depth of information shared are superiorly important in reducing non-performing loans. Four, the study is able to establish that employing the services of both private credit bureaus and public credit registries are most robust to dealing with bank non-performing loans. The study further found gross domestic product growth rate, gross domestic savings, inflation and interest rate spread to be significant determinants of non-performing loans to a large extent.

These findings have policy implications across the income bracket groupings for reducing non-performing loans. First, low income countries can emulate from the financial system of high income countries and tailor it to suit the present conditions of their system financial system so as to enable low income countries to reduce bank non-performing loans. Second, countries must do well to enact policies that deepen both coverage and depth of information shared as a combination of both is more robust to reducing bank non-performing loans. Third, a combination of both private credit bureau and public credit registry services can also be useful in dealing with bank non-performing loans. For the purpose of future research direction, researchers could examine the factors that enhance or improve credit information sharing. Again, researchers could replicate this study using country level data to test for consistency in findings.

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