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Credit information, consolidation and credit market performance: Bank-level evidence from developing countries

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Abstract

Paying particular attention to the degree of banking market concentration in developing countries, this paper examines the effect of credit information sharing on bank lending. Using bank-level data from African countries over the period 2004 to 2009 and a dynamic two-step system generalised method of moments (GMM) estimation, it is found that credit information sharing increases bank lending. The degree of banking market concentration moderates the effect of credit information sharing on bank lending. The results are robust to controlling for possible interactions between credit information sharing and governance.

JEL classification: D82; G21; G28; L13.

Keywords: Information sharing; Banking market concentration; Bank lending; Governance.

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1. Introduction

Information asymmetry and poor contract enforcement lead to suboptimal credit market equilibrium (Stiglitz & Weiss, 1981). To the extent that these problems are endemic in underdeveloped countries, financial sector underdevelopment in these

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countries could be attributed to poor credit information about borrowers. Credit information sharing is therefore expected to facilitate lending decisions (Bennardo et al., 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 hypothesised 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, the moderating effect of banking sector consolidation has been largely ignored.

In this paper I examine the effect of credit information sharing on bank lending in African countries. I further condition this effect on the extent of banking sector consolidation. This paper focuses on African countries for a number of reasons. The region exhibits record high levels of default. This, coupled with inadequate credit information and poor creditor rights protection, makes lending decisions within African banking markets a difficult task. Unsurprisingly, therefore, African banking markets remain dramatically underdeveloped, even compared to other developing countries (Honohan & Beck, 2007; Mylenko, 2007). Bank credit to the private sector in the region lags behind that of other regions. The region records the lowest credit penetration in the world (Mylenko, 2007) with less than 20% of households having access to formal banking services (Beck et al., 2009).

A key feature to which Africa's financial sector under-development may be attributed is weak contract enforcement. With rule of law, regulatory quality, and control of corruption well below the world average, it is unsurprising that it takes an extremely lengthy process to recover bad loans (Sacerdoti, 2005). The high credit risk translates into high interest spreads and margins (Beck et al., 2009).

With low banking depth and breadth, as well as high credit risk, the potential benefits of credit information have been appreciated in a few African countries. A few years ago, public credit registries and private credit bureaus were virtually non-existent. In recent times, significant efforts have been made to have operational information sharing systems in a number of African countries. In many of these countries, however, information sharing systems are in their infancy (e.g., Zambia, Nigeria and Ethiopia) and have low coverage. Several other countries are also in the process of establishing operational credit information sharing (e.g., Ghana, Tanzania and Uganda).

The effort to establish functional credit information sharing schemes in Africa is consistent with several years of financial sector reforms that have promoted banking competition in the region. With significant reforms across the African financial sectors over the past two decades,[1] the region has witnessed significant financial deepening and broadening in recent times (see Allen et al., 2012; Beck et al., 2009). Compared to developing countries in other regions, however, the pace of improvement is much slower (Allen et al., 2012). The years of reforms have also led to a downward trend in banking sector concentration, which has been characteristically high for the region (Fosu, 2013). Whilst the downward trend in concentration does not necessarily indicate improved competition (Boone et al., 2005, 2007; Boone, 2008; Demsetz, 1973), it does suggest that credit information is becoming more dispersed as the pool of borrowers per bank becomes smaller (Marquez, 2002).

In view of the above-mentioned features, this paper seeks to answer the following questions: first, how does credit information sharing affect lending in developing countries? Second, to what extent does the depth (or the characteristics) of credit information affect lending decisions? Third, to what extent is the effect of credit information sharing conditional on the degree of banking market concentration?

The results suggest that credit information sharing improves bank lending. It is also found that the depth of credit information is similarly important in increasing bank lending. Furthermore, it is found that the effect of credit information sharing is higher in less concentrated banking markets. The findings are robust to controlling for several measures of institutional quality and their possible interactions with credit information.

The paper contributes to the existing literature in several ways: first, the paper provides the first bank-level (supply side) evidence of the effect of credit information on credit allocation. Bank-level data ensures that individual banks' reactions to credit information sharing are not confounded by aggregate variation in credit allocation. In particular, bank-level data helps to isolate variations in credit allocation arising from (unobserved) heterogeneity of banks. Using aggregated credit data makes it impossible to isolate lending behaviour of specialised banks, especially those that are there to serve government motives. Second, this paper is the first to provide empirical evidence about the moderating effect of banking sector consolidation on the benefits of credit information sharing. Third, the paper further investigates the extent to which a wider range of institutional factors interacts with credit information sharing to impact on credit allocation. Finally, this is the first paper to attempt a comprehensive study of credit information sharing and bank lending in African countries.

The rest of this paper is organised as follows. Section 2 provides a review of

[1]Financial sector reforms are in the form of interest rate liberalisation, removal of credit ceilings, and privatisation of financial institutions, among others (see Allen et al., 2012).

the theoretical literature and empirical evidence that motivates this study. Section 3 outlines the research hypotheses. The data and variables used for the study are described in Section 5, whilst the empirical estimation methods are provided in Section 4. The findings of the study are discussed in Section 6. Section 7 concludes the study.

2. Literature review

This section provides a review of the theoretical and empirical literature that motivates this study. A strand of literature motivating the relationship between credit information sharing and credit market outcome (e.g., Behr & Sonnekalb, 2012; Bennardo et al., 2010; Brown et al., 2009; Djankov et al., 2007; Love & Mylenko, 2003; Padilla & Pagano, 1997, 2000; Pagano & Jappelli, 1993) is reviewed first. This is then followed by a body of literature that suggests that banking market concentration or competition is of importance in the relationship between credit information sharing and bank lending decisions (e.g., Cetorelli & Peretto, 2000; Jappelli & Pagano, 2002; Marquez, 2002; Pagano & Jappelli, 1993; Petersen & Rajan, 1995).

2.1. Theory of credit information sharing and bank lending

Theory shows that credit information sharing impacts on credit market performance by reducing adverse selection in lending (Pagano & Jappelli, 1993), reducing moral hazard on the part of borrowers, thereby increasing borrower efforts (Padilla & Pagano, 1997, 2000), and reducing credit rationing in multiple bank lending (Bennardo et al., 2010).

Pagano & Jappelli (1993) show that credit information sharing reduces adverse selection in bank lending. In their model, credit information sharing helps increase the bankable population and possibly expand lending. In the absence of credit information, banks cannot distinguish between new pools of potential borrowers who are likely to repay and those who are likely to default. The authors show that in such a situation, since the new loan applicants might have borrowed from other banks in the past, information sharing can help the bank in question make the right decision to lend safely to credible new applicants. The overall impact on lending, however, depends on the extent to which increased lending to safe borrowers compensates for the reduced lending to risky borrowers. As information sharing also reduces informational rent in contestable banking markets, the resulting increase in competition can increase lending.

Information sharing may also induce more bank lending by reducing borrower hold-up problems. Credit information acquired by a bank today confers informational advantage, which permits it to extract higher interest rates from borrowers in the future. Padilla & Pagano (1997) show that, when banks commit to sharing credit information, the extraction of informational rent is restrained. This increases borrower effort and makes repayment more likely. With reduced default risk, interest rates decrease and lending, in turn, increases.

It is also argued that sharing default information may serve as a disciplinary device to encourage borrowers to repay their debt. Among other moral hazard situations, borrowers may prioritise potential returns from risky investments over incentives to repay (Myers, 1977). It is shown in Klein (1992), Vercammen (1995) and Padilla & Pagano (2000) that sharing default information encourages repayment. This is because sharing credit information allows borrowers who default to be blacklisted. As blacklisted borrowers may have difficulty getting credit in future, borrowers thus have an incentive to avoid default. The resulting reduction in default rates could reduce borrowing cost and increase lending. Padilla & Pagano (2000), however, argue that sharing only default information has the potential to increase lending; sharing information about borrower quality cannot increase lending since borrowing cost cannot be reduced any further due to the elimination of informational rent.

Moreover, credit information sharing may help reduce over-borrowing and its associated credit rationing in multiple bank lending (Bennardo et al., 2010). Aside from the higher implicit cost in multiple bank lending (Petersen & Rajan, 1994), borrowing from multiple banks induces opportunistic behaviour among borrowers, causing them to over-borrow. This behaviour can be costly to lenders. Hence, their natural response to this opportunistic behaviour is to ration credit, raise interest rates or deny credit. Bennardo et al. (2010) show that credit information sharing permits lenders to assess the outstanding debts of each borrower and lend safely. This mitigates the need for credit rationing and higher interest charges. Therefore, bank lending is expected to be higher in the presence of credit information sharing.

The above review shows that credit information can have a positive effect on bank lending, although borrower composition (Pagano & Jappelli, 1993) and the type of information shared (Padilla & Pagano, 2000) may also have a role to play. In the following sections, the literature that links the banking market concentration to the relationship is reviewed.

2.1.1. Interaction of competition and credit information sharing

Theory explains that, by reducing adverse selection, borrower hold-up problems and moral hazard, credit information sharing may help reduce default rate and increase lending. However, there is a strand of literature that suggests that the overall impact of credit information sharing depends to some extent on the degree of banking market concentration. This literature further suggests that banking market concentration may not always restrain access to credit in informationally asymmetric banking markets.

Literature on banking competition suggests that imperfect competition is associated with higher interest rate spread (Pagano, 1993) and also leads to a higher tendency to ration credit (Guzman, 2000), resulting in sub-optimal credit market performance. This conclusion is without regard to the fact that some level of banking market concentration may help to reduce the degree of information asymmetry in credit markets. In fact, Petersen & Rajan (1995) suggest that banking market concentration encourages long term relationships in banking, due to the potential for intertemporal surplus sharing. These relationships help banks acquire important credit information about borrowers, suggesting that information asymmetry is less of a problem in more concentrated or less competitive banking markets.

Another reason to suggest that credit information sharing may not be as beneficial in concentrated markets as in competitive markets is given by Cetorelli & Peretto (2000). They show that banks in concentrated markets are more likely to screen borrowers and lend efficiently than banks in competitive markets. This view is consistent with Marquez (2002). They argue that competitive banking markets have a small pool of borrowers per bank, suggesting that these markets have more dispersed credit information. Hence, the risk of adverse selection is much higher in competitive banking markets. In contrast, banks in consolidated banking markets have a large pool of borrowers and face a relatively low risk of adverse selection.

The points highlighted above suggest that, whilst credit information sharing may affect bank lending, banking market concentration may play a crucial role. The information needs of banks in highly concentrated banking markets should be very different from banks in less concentrated markets. Thus, it is important for empirical works to address this concern.

2.2. Empirical evidence

The relationship between credit information sharing and credit market performance has attracted some empirical attention, starting with Jappelli & Pagano (2002), who, in a cross-sectional study of 43 countries, show that credit information sharing increases bank lending to the private sector (as a ratio of gross domestic product). Given that the quality of institutional factors such as legal enforcement, which protects the rights of creditors, could possibly substitute for the availability of credit information, they further control for these factors and find effect of information sharing is stronger in poorer countries. Behr & Sonnekalb (2012), however, show that, whilst credit information sharing reduces default rates, it has no effect on the probability of a loan application's approval. This suggests that the channels through which credit information sharing impacts on overall lending need further attention.

Using firm-level data, Love & Mylenko (2003) show that firms' perceived financial constraint is lower and the share of bank financing higher in countries where private credit bureaus exist. The effect of public credit registries, however, is found to be statistically insignificant. Their findings further suggest that small and medium-sized firms have improved access to bank financing in the presence of private credit bureaus. Similar evidence is presented in Brown et al. (2009). Using a sample of 24 transitions countries in Eastern Europe and the former Soviet Union, they find that credit information sharing improves firms' access to credit and reduces the cost of borrowing. Again, their findings suggest that credit information may be more beneficial to informationally asymmetric firms and firms in countries with weak legal enforcement.

Given the theoretical prediction that credit information is relatively less asymmetric in highly concentrated banking markets, one would equally expect credit information sharing to have less effect on lending in more concentrated banking markets. Empirical evidence is, however, lacking in this respect. The informational advantage of concentrated banking markets is empirically weak given that some studies (e.g., Black & Strahan, 2002; Hannan, 1991) suggest a negative effect of concentration on financing, whilst others show a positive effect (e.g., Cetorelli & Gambera, 2001; Petersen & Rajan, 1995). It is worth noting, however, that the negative effect of concentration on access to finance is ameliorated by the presence of credit information sharing. This is empirically shown by Beck et al. (2004). This evidence suggests some degree of interaction between credit information sharing and banking market concentration. Nevertheless, it does not provide evidence on the direct effect of credit information sharing and how banking market concentration moderates it. Related evidence presented in Barth et al. (2009) suggest that, both information sharing and banking market competition reduce corruption in bank lending, and that the effect of competition is mitigated by credit information sharing. This current paper seeks to investigate the direct and the interaction effects of credit information sharing on bank lending. Also, by using bank-level data, which provides supply side evidence, this paper adds a new dimension to the literature.

To conclude this section, it is emphasised that, even though micro-level evidence provides an additional dimension to the literature, as it helps to control for heterogeneity at the firm level, the literature could be extended by analysing the relationship between credit information sharing and the supply of credit at the bank level. Besides providing supply side evidence, this approach helps to control for (unobserved) heterogeneity of banks, which otherwise could be confounded. Additionally, even though theory predicts that the information needs of banks may be less of a problem in concentrated banking markets, the existing empirical studies have not considered the possibility that the effect of credit information sharing may be moderated by banking market concentration. This study seeks to fill in these gaps.

3. Research hypotheses

Based on the theoretical predictions and empirical evidence about credit information sharing and credit market outcomes, two main testable hypotheses are formulated.

Given that the problems that credit information sharing is meant to address are endemic in the African banking market, one could expect its effect to be particularly high in the region. For instance, high levels of adverse selection problems are reflected in the record levels of default in African banking markets. Also, moral hazard problems should be particularly high given the weak legal enforcement in the region. Hence, by reducing the risk of adverse selection (Pagano & Jappelli, 1993) and moral hazard (Bennardo et al., 2010; Padilla & Pagano, 2000; Pagano & Jappelli, 1993), credit information sharing is expected to reduce default rates and the cost of borrowing and, at the same time, reduce credit rationing. This leads to the first hypothesis:

H1: *Credit information sharing has a positive effect on bank lending in African banking markets.*

Also, given that banks in concentrated markets face relatively less information asymmetries due to the incentives of long term customer relations (Petersen & Rajan, 1995), more efficient screening (Cetorelli & Peretto, 2000) and less dispersed credit information (Marquez, 2002), credit information sharing is expected to have less effect on lending in concentrated banking markets. Hence, a second hypothesis is formulated as follows:

H2: *The effect of credit information sharing on bank lending decreases with banking market concentration.*

4. Empirical model

In this section, empirical models are formulated to help address the main questions raised in this paper. In order to explore variations in bank lending over time, the paper adopts a panel data approach, which permits bank and country level variables to vary over time. Also, to allow for the possibility that bank lending may not have been observed under long-run equilibrium for any given year, a dynamic estimation approach is adopted to accommodate the possibility of partial adjustment towards equilibrium. Thus, the following baseline model is formulated:

$$
\begin{aligned}
Lending_{i,t} &= \alpha + \beta_1 Lending_{i,t-1} + \beta_2 Info_{j,t} + \beta_3 CR_{j,t} + \gamma' X_{i,t} \\
&\quad + \xi' Z_{j,t} + \varepsilon_{i,t}, \qquad (1)
\end{aligned}
$$

where $i \in j$ indicates the ith bank in country j; *Lending* is the credit market performance measure; CR is the concentration ratio of banking markets in each country; $Info$ is the information sharing index, which is alternately the credit information sharing dummy and the depth of credit information index; X is a set of other bank control variables; whilst Z represents a set of macroeconomic variables and governance indicators; α, β, γ and ξ are parameters; and ε_{it} is a composite error term including bank-fixed effects:

$$\varepsilon_{i,t} = \mu_i + \nu_{i,t}$$

where μ_i is bank-fixed effects and $\nu_{i,t}$, by assumption, is an independently and identically distributed component with zero mean and variance σ_v^2. The detailed definition and description of all variables are given in Section 5. Growth and profitability are treated as predetermined, rather than as strictly exogenous variables, due to possible feedback from past shocks.

Equation (1) permits a direct test of the first research hypothesis. In order to test the second research hypothesis, equation (1) is modified to include an interaction term between information sharing index and concentration ratio as follows:

$$
\begin{aligned}
Lending_{i,t} &= \alpha + \beta_1 Lending_{i,t-1} + \beta_2 Info_{j,t} + \beta_3 CR_{j,t} + \beta_4 Info_{j,t} \times CR_{j,t} \\
&\quad + \gamma' X_{i,t} + \xi' Z_{j,t} + \varepsilon_{i,t} \qquad (2)
\end{aligned}
$$

The total (or marginal) effect of credit information is obtained by differentiating equation (1) with respect to the information sharing variable, as follows:

$$\frac{\partial\left(Lending_{i,t}\right)}{\partial\left(Info_{i,t}\right)}=\beta_2+\beta_4 CR_{j,t} \tag{3}$$

Here, β_4 reflects the extent to which banking market concentration moderates the effect of credit information sharing.

Due to the presence of the interaction term, the effect of banking market concentration on bank lending also needs to be interpreted with caution; it is now given by

$$\frac{\partial\left(Lending_{i,t}\right)}{\partial\left(CR_{i,t}\right)}=\beta_3+\beta_4 Info_{j,t} \tag{4}$$

The estimation of equations (1) and (2) requires special attention to avoid endogeneity problems. First, the bank-fixed effects need to be wiped out. This can be achieved by first-differencing the equations. Next, the lagged dependent variables, by construction, are correlated with the differenced error terms. To circumvent this setback, Arellano & Bond (1991) propose the difference GMM estimator, which uses the lagged levels of the endogenous variables as instruments in the differenced equation. Assuming that the original error term, $\varepsilon_{i,t}$, is serially uncorrelated, and that the explanatory variables are weakly exogenous, the following moment conditions apply:

$$E\left(y_{i,t-s}\Delta\varepsilon_{i,t}\right)=0; for s\geq 2; t=3,...,T \tag{5}$$

$$E\left(\mathbf{X}_{i,t-s}\Delta\varepsilon_{i,t}\right)=0; for s\geq 2; t=3,...,T. \tag{6}$$

where **X** represents all the explanatory variables other than lagged lending.

As shown in Alonso-Borrego & Arellano (1999) and Blundell & Bond (1998), lagged levels of the explanatory variables can perform poorly as instruments for their first-differences, due possibly to persistence or measurement error. Hence, to improve efficiency, the equation in levels may be combined with the differenced equation to obtain a system of equations (Arellano & Bover, 1995; Blundell & Bond, 1998). In the system GMM, the variables in levels have as instruments the lagged first-difference of the corresponding variables. Additional orthogonality restrictions apply as follows[2]:

[2]Lagged differences other that the most recent ones are not used because they result in redundant

$$E\left(\Delta y_{i,t-s}\varepsilon_{i,t}\right) = 0; for s = 1. \tag{7}$$

$$E\left(\Delta \mathbf{X}_{i,t-s}\varepsilon_{i,t}\right) = 0; for s = 1. \tag{8}$$

Theoretically, the first-differenced equation may have first order serial correlation. Second order serial correlation in the differenced equation is, however, a cause for concern as it indicates possible first order serial correlation in the levels equation (Roodman, 2009). Hence, a formal test for this is performed. Next, a Hansen test of over-identifying restrictions is employed to test the validity of the over-identification restrictions. Finally, standard errors are corrected for finite sample bias using the two-step covariance matrix proposed by Windmeijer (2005).

5. Data

To estimate the specified models in Section 4, bank-level data consisting of 471 African banks over the period 2004 to 2009 is obtained from the BankScope database, which accounts for about 90% of all banks in each country.[3] The sample consists of all active banks with three or more years of consecutive observations.[4] Banks with negative values of equity and for which the dependent variable, the ratio of loans to total assets, is missing are dropped. Country-year observations with less than three banks are also excluded from the sample. The final sample contains about 2000 bank-year observations.

Credit information sharing data and macroeconomic data are obtained from the World Bank (2011) World Development Indicators (WDI). Governance data, including rule of law, regulatory quality and control of corruption, are obtained from Worldwide Governance Indicators (WGI), details of which are discussed in Kaufmann et al. (2011).

moment conditions (see Arellano & Bover, 1995).

[3]For a detailed sample breakdown see Table A.1. The sample of banks is from 35 African countries. Tunisia, Kenya, Egypt and Tanzania have relatively high number of banks in the sample. However, this is a fair representation of the population of banks in each country.

[4]The subsequent results, however, do not significantly change when non-active banks are included in the sample.

5.1. Bank-specific Variables

The models to be estimated (equations (1) and (2)) employ the bank-specific variables described and motivated in this subsection. The choice of variables and proxies is guided by the literature. Credit market performance is measured as the ratio of loans to total assets, as in Andrianova et al. (2011), Chen & Liu (2013) Demetriades & Fielding (2012), Kaufman (1966) and Weill (2011), as it captures banks' tendency to grant loans. Following the literature, the paper controls for other bank level variables, particularly profitability, deposit mix and the government share in ownership of each bank.

Following Demetriades & Fielding (2012) the paper controls bank profitability and the ownership share of government in each bank. Profitability is measured as net income as a percentage of total assets; it controls for managerial efficiency. Government share is the percentage of ownership share in each bank that is held by the government. This variable controls for the credit stabilisation function of government-owned banks (e.g., Micco & Panizza, 2006) and the possible distortion of optimal market outcomes (e.g., Cecchetti & Krause, 2001; Barth et al., 2001; La Porta et al., 2002).

Also in order to control for the extent to which banks are reliant on demand deposits the paper controls for deposit mix as in Chen & Liu (2013), Heggestad & Mingo (1976) and Micco et al. (2007). Banks with a very high deposit mix may be less competitive at generating time and savings deposits (Heggestad & Mingo, 1976). Deposit mix is measured as the percentage of demand deposits to total deposits. This variable controls for the extent to which banks are reliant on demand deposits; banks with a very high deposit mix may be less competitive at generating time and savings deposits (Heggestad & Mingo, 1976).

5.2. Information sharing variables

Credit information sharing is measured in either of the following ways: first, as a dummy variable equal to one for countries (and years) in which either a public credit registry or private credit bureau operates.[5] The second measure of credit information sharing utilises a credit information index, which goes beyond the mere existence of credit registries and examines the depth of information sharing.

The depth of information index ranges from zero to six (0-6), where higher figures indicate the availability of more credit information to help make lending decisions. The index is zero if the credit registry or private credit bureau is non-operational or its

[5] As explained in World Banks "Doing Business" database, these countries are those that have zero percentage coverage of adult population.

coverage is below 1% of the adult population. Otherwise, one point is given for each of the following features: public credit registry or private credit bureau distributes data on both firms and individuals; both positive and negative credit information are shared; data from retailers, utility companies and financial institutions are shared; at least two years of historical data are distributed; data are collected and distributed for loan amounts below 1% of income per capita; and the law permits borrowers to inspect their own data.

5.3. Banking market concentration

Banking market concentration is mainly the three-bank concentration ratio, measured as the share of assets of the largest three banks as a percentage of total banking assets. This measure of concentration is preferred over other alternative measures (five-bank concentration ratio and the Herfindahl-Hirschman Index). This is because the sample size changes over the sample period, which could result in measurement bias when the number of banks goes beyond the top three banks (see, Beck et al., 2006). For robustness checks, however, the findings are verified against the five-bank concentration ratio and the Herfindahl-Hirschman Index (HHI) as alternative concentration measures.

5.4. Macroeconomic and governance variables

To ensure that the relationship between lending and credit information sharing is not driven by some variations in the macroeconomic and institutional environment, the paper controls for macroeconomic and institutional variables. Following Altunbas et al. (2009), Andrianova et al. (2011) and Dinc (2005), the growth rate of gross domestic product (GDP), measured as the annual percentage change in real GDP is controlled for. GDP growth rate controls for possible changes in the demand for credit within a country (Altunbas et al., 2009) and the possible variations in the probability of adverse selection and moral hazards across business cycles (Andrianova et al., 2011).

Also, following the literature (Barth et al., 2009; Dinc, 2005; Love & Mylenko, 2003; Weill, 2011), inflation rate, measured as the annual percentage change in the GDP deflator, is controlled. Inflation rate controls for uncertainty in credit market.

As a final step, consistent with the literature (e.g., Andrianova et al., 2011; Demetriades & Fielding, 2012; Jappelli & Pagano, 2002), governance indicators of rule of law, regulatory quality and control of corruption are controlled for. Rule of law is an index that captures "the perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence" (Kaufmann et al., 2011, p. 223). This index ranges from -0.25 to 0.25. The world average of this index for the base year is 0. Hence, a positive value of the index for any country suggests that country's performance is above the world average. Thus, higher values of the index suggest higher regard for the rule of law.

Regulatory quality is an index that proxies for the "the perceptions of the ability of the government to formulate and implement sound policies and regulations that permit and promote private sector development" (Kaufmann et al., 2011, p. 223). Again, the world average for this index is 0, and higher values suggest better regulatory environments. Control of corruption is an index "that captures the perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as 'capture' by elites and private interests" (Kaufmann et al., 2011, p. 223). As is the case with the first two indices, the world average is 0, and higher values suggest firmer controls on corruption.

5.5. Summary statistic

Descriptive statistics for the main variables are presented in Table 1. The average of lending is about 49.4%, indicating that bank credit is less than 50% of bank assets. By international standards, this is relatively low.[6] On average, profitability of African banks as a percentage of assets is about 1.7%.[7] Deposit mix averages about 85.8%, indicating that African banks are funded predominantly by demand deposits. This suggests that most banks face higher funding risks. In terms of ownership, on average, about 11.3% of total banking assets in Africa are owned by governments. All the above-mentioned variables exhibit a significant amount of variations, as indicated by their large standard deviations.

The three-bank concentration ratio is 0.584, suggesting that, on average, the top three banks in each country control about 58% of total banking assets.[8] It is also clear that a significant number of countries have information sharing institutions, but the credit information sharing has substantially low depth, as shown by an average

[6] The average ratio of lending to assets reported in this study is relatively low compared to those reported in related studies. For example, Dinc (2005) and Weill (2008) record an international average of 54% and 56% respectively.

[7] The average profitability looks high by international standard, a result attributable mainly to a few countries such as Botswana, South Africa, Namibia, Morocco, Sudan, Nigeria, Sierra Leone, Ghana, Uganda, Ethiopia and Kenya.

[8] This ratio reflects the effects of several years of significant reforms across African banking markets, which have seen significant increase in the number of banks in these countries in recent times (Allen et al., 2011; Fosu, 2013; Senbet & Otchere, 2006).

depth of credit information index of 2.

The mean values of the governance variables are all negative, indicating that the quality of governance in Africa is substantially below the world average. These variables also exhibit substantial variations, as indicated by their standard deviations.

Table 2 presents the correlation matrix of the main variable. The alternate measures of credit information sharing are strongly correlated, but this poses no concern as they do not enter the regression at the same time. Likewise, the governance indicators enter the regression one at a time as they exhibit a very strong correlation with one another. With regard to the remaining variables, there is no evidence of multicollinearity.

6. Empirical results

This section presents the estimation results for equations (1) and (2), which permit us to test the main research hypotheses. In order to ascertain the sensitivity of the main results, a series of robustness checks is also carried out.

6.1. Main results

The main results of this paper are presented in Tables 3 and 5. The corresponding marginal effect analyses which help substantiate the test of the research hypothesis are presented in Tables 4 and 6, respectively. In Table 3, the information sharing dummy variable is used as a measure of the availability of credit information through information sharing, whilst in Table 5 the depth of credit information index is used. In all the results presented here and in subsequent sections, the maximum lag dependent variables are restricted to one in order to restrain the number of moment conditions. The lag dependent variables are positive and significant; the Hansen test p-values are all well above 0.1, justifying the validity of the over-identification restriction; and, finally, the absence of second-order serial correlation is not rejected. Thus, the use of a dynamic model is appropriate.

6.1.1. Results using the credit information sharing dummy

The results presented in Table 3 show that credit information increases bank lending in developing countries. Starting from Model 1 (relating to equation (1) without controlling governance), it can be seen that the coefficient on $Information\ sharing$ is positive and highly significant. It suggests that banks in countries that share credit information lend approximately 4.72% more than their counterparts in countries without credit information sharing. In other words, countries that switch to an information sharing regime can expect to increase bank lending by about 4.72%. This finding provides support for the first research hypothesis (Hypothesis 1). The finding here is largely consistent with macro- and firm-level evidence provided in Brown et al. (2009), Djankov et al. (2007), Jappelli & Pagano (2002) and Love & Mylenko (2003).

As regards the control variables, the results in Model 1 of Table 3 also suggest that banking market concentration, generally, significantly impedes bank lending. This evidence is broadly consistent with Black & Strahan (2002) and Hannan (1991). Also, profitable banks lend more than less profitable banks. This may be attributed to the notion that more profitable banks have more efficient management. Consistent with Weill (2011), it is also seen that banks that depend more on demand deposits lend less. It is possible that, being less competitive in generating funds from other sources increases bank risk aversion. The effect of government share in the ownership of banks does not significantly affect bank lending. Whilst its coefficient is negative, it is statistically insignificant. This could possibly be because government banks are becoming less active in credit markets in developing countries as many of these countries experience high growth rates (see Micco & Panizza, 2006). Growth rate of GDP is positively associated with more bank lending. This can be attributed to the possibility that higher growth rate induces confidence in credit markets. High rates of inflation, on the other hand, decrease bank lending.

Model 2 of Table 3 shows the results for the estimation involving the interaction term between information sharing and concentration (i.e., equation (2)). The control variables retain their signs and significance. Banking market concentration is significant only through its interaction with information sharing. Thus, the effect of concentration on bank lending is insignificant when there is no credit information sharing, but significantly negative when credit information is shared. Impliedly, barring the information advantage of concentrated banking markets, concentration can have a detrimental effect on bank lending. Stated differently, banking concentration may be less harmful in an informationally asymmetric banking environment. This finding is more or less inconsistent with (Beck et al., 2004).

As before, credit information sharing is seen to impact positively and significantly on bank lending, as the coefficient on $Information\ sharing$ remains positive. However, due to the presence of the interaction term, the results need to be interpreted carefully. The coefficient on the interaction term, $Informationsharing \times Concentration$, is negative and statistically significant, suggesting that the positive effect of credit information sharing is a decreasing function of banking market concentration. Thus, the findings suggest that information asymmetry is less of a problem in more concentrated banking markets, making credit information sharing less effective at increasing lending. This finding provides support for the second research hypothesis (Hypothesis 2), but the detailed marginal effect analysis that follows shortly will help corroborate this. Models 3–9 extend the analysis by controlling for governance indicators of *rule of law* (Models 3–4), *regulatory quality* (Models 5–6) and *control of corruption* (Models 7–8). The results remain unchanged, whilst the governance indicators appear significant with the expected sign.

Evaluating the moderating effect of concentration on the relationship between credit information sharing and bank lending, Table 4 suggests that credit information sharing can increase bank lending by between 2.60% and 5.07%, depending on the degree of banking market concentration. Applying equation 3 to Model 2 of Table 3, where no governance indicator is controlled for, a switch to an information sharing regime is associated with a 5.06% increase in bank lending when the banking market concentration is at the 25th percentile. This effect decreases to 4.27% and 2.64% when concentration is at the 50th and 75th percentiles, respectively. The marginal effect analysis yields similar results when applied to the models in which governance indicators are controlled for (i.e., Models 4, 6, and 8), as shown in the table. In fact, the difference between the effect of credit information sharing at the 25th percentile, on the one hand, and at the 75th percentile, on the other hand, is at least 2.32%. Hence, it can be concluded safely that the benefit of credit information sharing decreases with banking market concentration. This evidence strengthens the support for Hypothesis 2.

The next set of results focuses on the depth of credit information index, rather than the mere presence of information sharing. This is an important addition in view of the fact that the depth of information sharing differs considerably across countries.

6.1.2. Results using the depth of credit information index

Table 5 presents the results in which the depth of credit information index is used in place of the information sharing dummy. Since the characteristics of credit information sharing differ between countries and time periods, the depth of credit information index is likely to capture more information than the information sharing dummy variable.

The findings are consistent with those presented in Subsection 6.1.1. In Model 1 of Table 5 it can be seen that a one-unit increase in the depth of credit information index increases bank lending by about 0.86%. The effect is highly statistically significant (at the 1% level). Hence, switching from a regime without credit information sharing to a regime with fully-fledged credit information sharing can increase bank lending by up to 5.16%. The finding is consistent with the models that control for governance indicators (Models 3, 5 and 7). This finding, again, provides support for Hypothesis 1.

The models that incorporate the interaction term between the depth of credit information index and banking market concentration (Models 2, 4, 6 and 8) give similar results to those presented earlier. Again, the depth of credit information index remains positive and statistically significant, whilst the interaction term is significantly negative. Thus, the results further suggest that a higher depth of credit information is associated with higher bank lending, but the increased lending may not be by as much in concentrated banking markets as in less concentrated banking markets. Again, this finding is robust across different model specifications. The negative coefficients of the interaction terms also suggest that the overall effect of banking market concentration on bank lending is negative.

As in the preceding section, in order to measure the moderating effect of concentration on credit information sharing, the interaction term is evaluated at the 25th, 50th and 75th percentiles of concentration. Table 6 presents this marginal effect analysis. In the model that does not control for any governance indicator (Model 2 of Table 3), a one-unit increase in the depth of credit information index increases bank lending by 0.95%, 0.656% and 0.062% at the 25th 50th and 75th percentiles, respectively. This clearly shows that the lending-enhancing effect of credit information sharing decreases with banking market concentration, thus providing support for Hypothesis 2. Similar results are reported for the models controlling for governance indicators.

6.2. Robustness checks

A natural progression, at this stage, is to assess the robustness of the above findings. In particular, the possibility of further interactions between information sharing and governance is investigated. This is followed by addressing the possibility of endogeneity problems. Next, the effects of using alternative estimation methods, on the one hand, and alternative measures of concentration, on the other hand, are analysed.

6.2.1. Extensions - interactions with governance indicators

It may be argued that good quality governance may be a substitute for credit information sharing. For instance, credit information sharing may be more useful in banking markets with less legal enforcement (Jappelli & Pagano, 2000, 2002). Hence, the models above are extended to include interactions with governance indicators of the rule of law, regulatory quality and control of corruption. The results are presented in Table 7; they are similar to those presented earlier in Subsection 6.1.

The effects of governance on bank lending now need to be equally interpreted with caution, given the presence of their interaction with information sharing. The models employing the information sharing dummy suggest that a one-unit (corresponding to one standard deviation in the worldwide sample) increase in governance increases bank lending by between 3.24% and 4.63% when there is no information sharing scheme, depending on the governance indicator used. When credit information sharing exists, the effect is up to 1.86%. Similarly, when the depth of credit information index is employed, a one-unit increase in governance will improve bank lending by up to 3.88% when the depth of credit information index is 0. However, at the median depth of credit information index, a one-unit increase in governance will improve bank lending by up to 1.93%.

Table 7 shows that credit information sharing impacts positively on bank lending. The coefficients of the interaction term between the credit information sharing and concentration (Models 1, 3 and 5) remain significantly negative. Also, the additional interactions between credit information sharing and governance indicators are negative and statistically significant. The findings are consistent when the depth of credit information index is employed as the measure of information sharing. In Models 2, 4 and 6, the depth of credit information index has a statistically significant coefficient, whilst the interaction terms all have statistically significant negative coefficients. Thus, whilst providing support for the findings that credit information sharing impacts positively on bank lending and that this effect decreases with concentration, the results further show that the benefits of credit information sharing are less in countries with robust governance compared with countries with more lax governance.

The marginal effect analysis presented in Table 8 shows that, by holding the rule of law at the 25th percentile, a switch to an information sharing regime will increase bank lending by about 5.95% if concentration is at the 25th percentile, but by 3.90% if concentration is at the 75th percentile. However, at the 75th percentile of the rule of law, the effect of information sharing will be a 3.41% and 1.36% increase in bank lending if concentration is at the 25th and 75th percentiles, respectively. This analysis confirms that sharing credit information can help boost bank lending, and that the effect is not as great in more concentrated banking markets as it is in less concentrated banking markets.

6.2.2. Endogenous credit information

The next robustness check performed in this paper is in respect of possible reverse causality between credit information sharing and bank lending. This endogeneity problem is less likely to apply in this study since it is conducted at individual bank level whilst credit information sharing decisions are at the country level. It is unlikely that an individual bank's lending decision influences the information sharing policy at the national level. Besides, over the sample period, majority (89%) of the countries in the sample maintained their information sharing regime, making reverse causality less likely.

The above notwithstanding, an attempt is made to re-estimate the model assuming information sharing is endogenous. The following are employed as external instruments for the credit information variables: religious composition, ethnocentric fractionalisation, legal origin and urbanisation.[9] Urbanisation, measured as percentage of urban population to total population, is obtained from the World Bank (2011).[10] Ethnocentric fractionalisation, legal origin and religious compositions are shown to be significant determinants of the establishment of information sharing schemes (see Djankov et al., 2007), and have been used as instruments for information sharing in recent papers (Barth et al., 2009; Houston et al., 2010). Urbanisation has also been used in Buyukkarabacak & Valev (2012) as an instrument for information sharing on the grounds that information travels less effectively in urban areas, making credit information sharing more likely in more urbanised countries.

Having included in the regression other variables capturing institutional settings, the instruments may be assumed to satisfy the standard exclusion criteria. In the first stage of the regression all the instruments significantly affect credit information sharing.[11]

The findings presented in Tables 9 and 10 are consistent with those presented earlier. Table 9 presents the results for the credit information sharing dummy. Despite the apparent differences in the magnitudes of the coefficients, information sharing has a significantly positive coefficient whilst the interaction term remains significantly negative across all models. In fact, the marginal effect analysis shows that, at the 25th percentile of concentration, sharing credit information can increase bank lending by up to 6.69%, about 1.63% higher than the case where information sharing is treated as exogenous. At the 50th percentile, bank lending is 4.36% higher when credit information is shared. This compares to 4.27% in the case where information

[9]Religious composition (the percentages of Protestant, Catholic and Muslim populations to total population), ethnocentric fractionalisation (a measures the extent of ethnic diversity) and legal origin (an indicator of the origin of a country's legal system) are obtained from La Porta et al. (1999).

[10]There are concerns that urbanisation may have a direct impact on lending, rendering it invalid as an instrument. To address this issue I drop urbanisation from the instrument set, and the results remain mostly unchanged. Additionally, when including urbanisation in the main estimations as an explanatory variable, it enters insignificantly.

[11]First stage regression results are available upon request.

sharing is treated as exogenous.[12] Thus, the findings are consistent at the relevant levels of banking market concentration.

Table 10 reports the results for the case where the depth of credit information index is treated as endogenous. The findings are highly consistent. The depth of credit information index has a positive coefficient and it is statistically significant. The interaction between this variable and concentration is significantly negative, as before. This corroborates the earlier findings that credit information sharing increases bank lending, and that the rise in bank lending resulting from credit information sharing decreases with banking market concentration. In fact, marginal effect analysis yields predictions very close to those presented earlier.

6.2.3. Alternative estimation methods

The robustness of the findings to alternative estimation methods is assessed in this section. Specifically, ordinary least square (OLS) method is employed.[13] It is noteworthy that the inclusion of the lagged dependent variable makes this alternative estimation method inefficient. The results are presented in Tables 11 and 12. The adjusted R^2 shown in the results tables suggests that about 80% of the variations in bank lending are explained by the explanatory variables. The lagged dependent variable is also significant, justifying the use of a dynamic estimation method. Its coefficients are also relatively larger in magnitude than those presented in the main results (Tables 3 and 5).

Table 11 presents the OLS results for the models using the information sharing dummy. The results are qualitatively similar to those obtained under the dynamic system GMM estimation. The coefficient of information sharing is positive across all the models. It is also significant across all models without interaction terms except when the governance indicator is the regulatory quality. When the interaction term is included, information sharing remains positive and significant, whilst the interaction term is consistently negative across all models.

Highly consistent results are found when the depth of credit information index is employed. Table 12 shows that the depth of credit information index is positive and highly significant under all models. The interaction term is also consistently negative and highly significant across all models. These findings lend support to the research hypotheses.

[12] A separate marginal effect analysis is not reported for brevity of this paper. It is available upon request.

[13] Given that the information sharing variables exhibit little within variation, fixed effect (within) estimation would yield particularly inflated variance, rendering the explanatory power of the vari-

6.2.4. Other sensitivity checks

Additional sensitivity checks are also carried out. The robustness of the findings to alternative measures of competition is also assessed. First, the three-bank concentration ratio is replaced with the five-bank concentration ratio, and, second, the Herfindahl-Hirschman Index (HHI) is used as the alternative measure of concentration. Both yield consistent results. Third, controlling for log of total assets and capital ratio as endogenous variables yields consistent results, but these variables appear statistically insignificant. Additionally, controlling for liquid assets as a percentage of total assets, a proxy of risk aversion, does not change the findings.

Moreover, the sensitivity of the findings is assessed against the possibility that some types of banks have different lending behaviour than others. As a step to assessing this possibility, specialised government credit institutions and multi-lateral government banks, as well as investment banks are (alternatively and jointly) dropped from the sample. The results are highly consistent with the findings reported above.

Finally, a subsample containing only countries that share credit information is obtained, and the depth of credit information index used as the measure of credit information. This is to help identify the true effect of having a robust credit information sharing scheme, rather than merely having such a scheme. The estimations from this subsample yield consistent results.

7. Conclusion

Using bank-level data, the results from this paper suggest that credit information sharing increases bank lending. Moreover, this study finds that the increases in bank lending arising from credit information sharing decrease with banking market concentration. The results are robust to alternative measures of credit information sharing and banking market concentration.

Whilst banking market concentration may signal less dispersion of credit information, the evidence in this paper suggests that this informational advantage does not outweigh the distortion of optimal credit market performance caused by banking market concentration. Given the wave of regulatory reforms across many banking markets in developing countries, which have already opened up the domestic banking markets for entry of new and foreign banks, the evidence suggests that embracing or deepening credit information sharing will help boost financial development in these countries.

ables weak.

The evidence further suggests that policy makers cannot necessarily view quality governance as a perfect substitute for ensuring better access to credit information. Even though the benefits of credit information sharing decrease with the quality of governance, some positive benefits still accrue from information sharing even at very high levels of governance. This is consistent with the fact that, even in developed countries where rule of law, for example, is robust, credit information sharing is advanced. Hence, the findings of this paper implore developing countries to strive to achieve effective and efficient credit information sharing schemes alongside the ongoing regulatory reforms and the promotion of quality governance.

Appendix A.

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Table 1: Descriptive statistics

Variable	Mean	Std. Dev.	25th percentile	50th percentile	75th percentile	N
Lending	49.389	21.218	34.252	49.377	63.745	2296
Profitability	1.748	3.469	0.716	1.630	2.835	2288
Deposit mix	85.788	22.696	84.272	94.644	99.352	2113
Government share	11.266	26.764	0	0	0.17	1949
GDP growth	5.214	3.943	3.279	5.609	6.899	1785
Inflation	8.467	6.238	3.892	7.448	11.536	2271
Concentration	0.584	0.164	0.449	0.536	0.7118	2296
Credit information sharing	0.709	0.454	0	1	1	2296
Depth of credit information	2.041	1.978	0	2	4	2296
Rule of law	−0.43	0.586	−0.882	−0.374	0.029	2296
Regulatory quality	−0.335	0.519	−0.632	−0.320	−0.057	2296
Control of corruption	−0.465	0.554	−0.891	−0.530	−0.091	2296

This table presents the descriptive statistics for the data. The sample comprises 471 banks over the period 2004 to 2009. *Lending* is the percentage of loans to total assets; *Profitability* is the is the percentage of net income to total assets; *Deposit mix* is the percentage of demand deposits to total deposits; *Government share* is the percentage of ownership share in each bank that is held by the government; *GDP growth* is the annual percentage change in real GDP; *Inflation* is the annual percentage change in the GDP deflator; *Concentration* is the three-bank concentration ratio, measured as the share of assets of the largest three banks as a percentage of total banking assets; *Credit information sharing* is a dummy variable equal to one for countries (and years) in which either public credit registry or private credit bureaus operate; *Depth of credit information* is an index that captures the depth of credit information. *Rule of law*, *Regulatory quality* and *Control of corruption* are indicators capturing the quality of governance defined in detail in Subsection 5.4.

Table 2: Correlation matrix

Variables	1	2	3	4	5	6	7	8	9	10	11	12
1 Lending	1.000											
2 Profitability	−0.003	1.000										
3 Deposit mix	−0.295	0.035	1.000									
4 Government share	−0.003	−0.010	−0.019	1.000								
5 GDP growth	−0.154	−0.014	−0.003	−0.002	1.000							
6 Inflation	−0.251	0.018	0.143	−0.002	0.198	1.000						
7 Concentration	−0.168	−0.044	0.134	0.007	0.106	−0.070	1.000					
8 Credit information sharing	0.319	−0.024	−0.144	0.070	−0.215	−0.246	−0.084	1.000				
9 Depth of credit information	0.260	0.056	−0.132	0.099	−0.246	−0.035	−0.381	0.660	1.000			
10 Rule of law	0.299	0.044	−0.180	0.052	−0.190	−0.207	−0.192	0.246	0.410	1.000		
11 Regulatory quality	0.340	0.092	−0.149	0.019	−0.253	−0.202	−0.394	0.352	0.573	0.851	1.000	
12 Control of corruption	0.304	0.079	−0.131	0.053	−0.244	−0.221	−0.138	0.274	0.449	0.898	0.847	1.000

This table presents the unconditional correlation coefficient between any pair of variables. *Credit information sharing* and *Depth of credit information* are alternative measures of the availability of credit information, and therefore they do not simultaneously enter the same regression. Likewise, *Rule of law*, *Regulatory quality* and *Control of corruption* are alternative measures of governance and do not simultaneously enter the same. All variables are as described in Table 1 and Subsection 5.4.

Table 3: Credit information sharing, concentration and bank lending: dynamic two-step system GMM estimation

Dependent variable: Lending	Governance indicator							
	None		*Rule of law*		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
$Lending_{-1}$	0.626***	0.656***	0.608***	0.635***	0.613***	0.593***	0.648***	0.642***
	(0.065)	(0.065)	(0.063)	(0.062)	(0.065)	(0.066)	(0.064)	(0.063)
Profitability	0.548***	0.488***	0.528***	0.528***	0.438***	0.474***	0.278**	0.483***
	(0.175)	(0.158)	(0.181)	(0.184)	(0.156)	(0.169)	(0.134)	(0.153)
Deposit mix	−0.061***	−0.052**	−0.060**	−0.049**	−0.056**	−0.061**	−0.054***	−0.051**
	(0.023)	(0.022)	(0.024)	(0.022)	(0.022)	(0.024)	(0.021)	(0.022)
Government share	−0.015	−0.019	−0.016	−0.017	−0.017	−0.015	−0.019	−0.017
	(0.014)	(0.014)	(0.016)	(0.015)	(0.015)	(0.016)	(0.014)	(0.015)
Inflation	−0.235***	−0.266***	−0.243***	−0.259***	−0.269***	−0.241***	−0.228***	−0.238***
	(0.059)	(0.059)	(0.058)	(0.056)	(0.057)	(0.059)	(0.055)	(0.057)
GDP growth	0.199*	0.271**	0.218*	0.319***	0.300***	0.262**	0.222**	0.261**
	(0.112)	(0.114)	(0.116)	(0.111)	(0.110)	(0.117)	(0.112)	(0.116)
Concentration	−7.933***	0.013	−7.849***	−0.405	−4.906**	0.996	−6.375***	0.081
	(2.597)	(3.742)	(2.538)	(3.964)	(2.388)	(4.136)	(2.330)	(3.976)
Information sharing	4.720***	9.220***	4.683***	9.910***	3.628***	9.109***	3.727***	9.250***
	(1.207)	(2.833)	(1.167)	(2.788)	(1.084)	(2.761)	(1.081)	(2.765)
Information sharing x Concentration		−9.238**		−9.866**		−8.849*		−9.346**
		(4.387)		(4.523)		(4.659)		(4.487)
Governance			1.266*	1.095*	2.859***	2.676***	1.352*	1.522**
			(0.680)	(0.657)	(0.900)	(0.956)	(0.699)	(0.695)
Constant	24.784***	18.721***	26.086***	19.675***	25.191***	22.456***	23.930***	19.823***
	(5.129)	(5.217)	(5.023)	(5.348)	(4.920)	(5.653)	(4.962)	(5.393)
No. of observations	1421	1421	1421	1421	1421	1421	1421	1421
Hansen test p-value	0.286	0.465	0.338	0.655	0.667	0.423	0.714	0.476
Resid. AR(2) test p-value	0.721	0.776	0.740	0.807	0.856	0.766	0.781	0.760

This table shows the dynamic system GMM estimation results for the effect of credit information on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4 Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses.

* Indicates significance at 10%.

** Indicates significance at 5%.

*** Indicates significance at 1%.

Table 4: Effect of credit information sharing at specified levels of concentration

Concentration at:	25% (0.449)	50% (0.536)	75% (0.712)	Change between 25% and 75%	Based on regression
Governance indicator:					
None	5.069***	4.265***	2.644**	2.424**	Table 3, column 2
	(1.302)	(1.170)	(1.263)	(1.151)	
Rule of law	5.476***	4.618***	2.887**	2.589**	Table 3, column 4
	(1.205)	(1.088)	(1.258)	(1.187)	
Regulatory quality	5.132***	4.363***	2.810**	2.322*	Table 3, column 6
	(1.187)	(1.104)	(1.355)	(1.223)	
Control of corruption	5.050***	4.237***	2.597**	2.453**	Table 3,column 8
	(1.226)	(1.120)	(1.294)	(1.177)	

This table shows the marginal effect analysis of the results presented in Tables 3. Marginal effects are evaluated at the 25th, 50th and 75th percentiles of concentration. Standard errors are in parentheses.
* Indicates significance at 10%.
** Indicates significance at 5%.
*** Indicates significance at 1%.

Table 5: Depth of credit information, concentration and bank lending: dynamic two-step system GMM estimation

Dependent variable: Lending

	Governance indicator							
	None		*Rule of law*		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lending_{-1}	0.664***	0.681***	0.651***	0.678***	0.641***	0.671***	0.650***	0.677***
	(0.061)	(0.061)	(0.060)	(0.056)	(0.061)	(0.056)	(0.061)	(0.056)
Profitability	0.422***	0.403***	0.408***	0.419***	0.373***	0.391***	0.390**	0.397***
	(0.152)	(0.142)	(0.155)	(0.140)	(0.142)	(0.131)	(0.153)	(0.135)
Deposit mix	−0.052**	−0.048**	−0.052**	−0.047**	−0.055**	−0.050**	−0.053**	−0.048**
	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.022)
Government share	−0.020	−0.021	−0.020	−0.020	−0.019	−0.019	−0.020	−0.020
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Inflation	−0.323***	−0.307***	−0.322***	−0.301***	−0.313***	−0.290***	−0.317***	−0.293***
	(0.064)	(0.063)	(0.062)	(0.060)	(0.063)	(0.060)	(0.062)	(0.059)
GDP growth	0.292**	0.307***	0.297***	0.307***	0.308***	0.316***	0.299***	0.312***
	(0.115)	(0.118)	(0.114)	(0.116)	(0.114)	(0.115)	(0.115)	(0.116)
Concentration	−3.510	3.151	−3.734*	2.926	−2.233	4.148	−3.912*	3.248
	(2.158)	(2.732)	(2.185)	(2.762)	(2.200)	(2.768)	(2.219)	(2.768)
Depth of information	0.856***	2.471***	0.807***	2.437***	0.610***	2.253***	0.762***	2.501***
	(0.205)	(0.656)	(0.209)	(0.658)	(0.208)	(0.663)	(0.203)	(0.654)
Depth of information x Concentration		−3.386***		−3.421***		−3.393***		−3.667***
		(1.236)		(1.243)		(1.261)		(1.245)
Governance			0.754	0.587	2.384**	1.967**	1.125	1.064
			(0.694)	(0.655)	(0.992)	(0.931)	(0.714)	(0.663)
Constant	21.566***	16.651***	22.736***	17.203***	23.534***	17.870***	23.314***	17.486***
	(4.902)	(4.898)	(4.935)	(4.773)	(4.942)	(4.794)	(5.015)	(4.787)
No. of observations	1421	1421	1421	1421	1421	1421	1421	1421
Hansen test p-value	0.396	0.341	0.447	0.575	0.506	0.637	0.438	0.583
Resid. AR(2) test p-value	0.911	0.894	0.920	0.895	0.959	0.920	0.912	0.886

This table shows the dynamic system GMM estimation results for the effect of credit information on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4 Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses.

* Indicates significance at 10%.

** Indicates significance at 5%.

*** Indicates significance at 1%.

Table 6: Effect of depth of credit information sharing at specified levels of concentration

Concentration at:	25% (0.449)	50% (0.536)	75% (0.712)	Change between 25% and 75%	Based on regression
Governance indicator:					
None	0.950***	0.656***	0.062	0.888***	Table 5, column 2
	(0.210)	(0.201)	(0.322)	(0.324)	
Rule of law	0.900***	0.602***	0.002	0.898***	Table 5, column 4
	(0.207)	(0.199)	(0.323)	(0.326)	
Regulatory quality	0.728***	0.433**	−0.162	0.890***	Table 5, column 6
	(0.209)	(0.202)	(0.330)	(0.331)	
Control of corruption	0.853***	0.534***	−0.111	0.962***	Table 5,column 8
	(0.199)	(0.192)	(0.321)	(0.327)	

This table shows the marginal effect analysis of the results presented in Table 5. Marginal effects are evaluated at the 25th, 50th and 75th percentiles of concentration. Standard errors are in parentheses.
** Indicates significance at 5%.
*** Indicates significance at 1%.

Table 7: Credit information, concentration and bank lending - extensions: dynamic two-step system GMM estimation

Dependent variable: Lending

	Governance indicator					
	Rule of law		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Lending_{-1}	0.626***	0.666***	0.609***	0.662***	0.644***	0.668***
	(0.068)	(0.065)	(0.063)	(0.068)	(0.061)	(0.065)
Profitability	0.476***	0.422***	0.474***	0.405***	0.491***	0.403***
	(0.162)	(0.136)	(0.169)	(0.129)	(0.160)	(0.142)
Deposit mix	−0.052**	−0.045**	−0.054**	−0.045**	−0.052**	−0.045**
	(0.022)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)
Government share	−0.018	−0.020	−0.017	−0.019	−0.020	−0.021
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.015)
Inflation	−0.258***	−0.311***	−0.269***	−0.296***	−0.263***	−0.302***
	(0.059)	(0.067)	(0.056)	(0.066)	(0.056)	(0.065)
GDP growth	0.230**	0.264**	0.329***	0.272**	0.286**	0.278**
	(0.116)	(0.121)	(0.114)	(0.121)	(0.113)	(0.121)
Concentration	−2.131	2.898	1.317	5.281*	−1.567	3.072
	(4.298)	(2.897)	(3.862)	(2.870)	(3.942)	(2.960)
Information sharing	7.006**		8.261***		6.804**	
	(3.012)		(2.752)		(2.907)	
Information sharing x Concentration	−7.815*		−10.373**		−7.851*	
	(4.636)		(4.485)		(4.413)	
Information sharing x Governance	−2.780**		−2.762*		−2.294*	
	(1.379)		(1.650)		(1.367)	
Depth of information		2.431***		2.749***		2.345***
		(0.677)		(0.731)		(0.696)
Depth of information x Concentration		−3.805***		−4.622***		−3.827***
		(1.279)		(1.406)		(1.320)
Depth of information x Governance		−0.870**		−0.975**		−0.695**
		(0.398)		(0.461)		(0.346)
Governance	3.244***	2.443**	4.630***	3.879***	3.324***	2.991**
	(1.238)	(1.123)	(1.473)	(1.428)	(1.254)	(1.166)
Constant	23.124***	18.584***	22.497***	17.997***	22.265***	18.896***
	(6.042)	(5.450)	(5.527)	(5.395)	(5.485)	(5.422)
No. of observations	1421	1421	1421	1421	1421	1421
Hansen test p-value	0.366	0.209	0.757	0.195	0.716	0.171
Resid. AR(2) test p-value	0.740	0.890	0.812	0.892	0.766	0.882

This table shows the dynamic system GMM estimation results for the effect of credit information on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4 Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses.

* Indicates significance at 10%.

** Indicates significance at 5%.

*** Indicates significance at 1%.

Table 8: Effect of credit information sharing at specified levels of concentration and governance

Concentration at:	25% (0.449)	50% (0.536)	75% (0.712)	Change between 25% and 75%	Based on regression
Rule of law at:					
25% (-0.882)	5.946*** (1.387)	5.267*** (1.328)	3.896** (1.560)	2.051* (1.217)	Table 7, column 1
50% (-0.364)	4.534*** (1.258)	3.855*** (1.141)	2.484* (1.132)	2.051* (1.217)	Table 7, column 1
75% (0.029)	3.412** (1.419)	2.733** (1.278)	1.362 (1.363)	2.051* (1.217)	Table 7, column 1
Regulatory quality at:					
25% (-0.631)	5.345*** (1.225)	4.444*** (1.105)	2.624** (1.259)	2.722** (1.177)	Table 7, column 3
50% (-0.320)	4.483*** (1.138)	3.581*** (1.025)	1.760 (1.217)	2.722** (1.177)	Table 7, column 3
75% (-0.057)	3.757**** (1.239)	2.855** (1.148)	1.035 (1.344)	2.722** (1.177)	Table 7, column 3
Control of corruption at:					
25% (-0.894)	5.320*** (1.274)	4.637*** (1.189)	3.260** (1.374)	2.060* (1.158)	Table 7, column 5
50% (-0.521)	4.490*** (1.171)	3.808*** (1.049)	2.430** (1.204)	2.060* (1.158)	Table 7, column 5
75% (-0.091)	3.489*** (1.313)	2.800** (1.174)	1.423 (1.250)	2.060* (1.158)	Table 7, column 5

This table shows the marginal effect analysis of the results presented in Table 7. Marginal effects are evaluated at the 25th, 50th and 75th percentiles of concentration and governance indicators. Standard errors are in parentheses.

* Indicates significance at 10%.

** Indicates significance at 5%.

*** Indicates significance at 1%.

Table 9: Endogenous credit information sharing, concentration and bank lending: dynamic two-step system GMM estimation

Dependent variable: Lending	Governance indicator							
	None		*Rule of law*		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lending_{-1}	0.779***	0.754***	0.769***	0.750***	0.753***	0.705***	0.764***	0.744***
	(0.061)	(0.056)	(0.061)	(0.057)	(0.062)	(0.060)	(0.060)	(0.055)
Profitability	0.536***	0.453**	0.514**	0.447**	0.460**	0.412***	0.478**	0.417**
	(0.203)	(0.186)	(0.205)	(0.189)	(0.202)	(0.139)	(0.201)	(0.188)
Deposit mix	−0.029	−0.030*	−0.029	−0.030*	−0.033*	−0.041**	−0.030*	−0.029*
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.019)	(0.018)	(0.018)
Government share	−0.012	−0.017	−0.013	−0.017	−0.013	−0.018	−0.013	−0.017
	(0.010)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.011)	(0.012)
Inflation	−0.160***	−0.176***	−0.162***	−0.179***	−0.169***	−0.216***	−0.164***	−0.181***
	(0.055)	(0.056)	(0.055)	(0.056)	(0.055)	(0.061)	(0.055)	(0.056)
GDP growth	0.216*	0.237**	0.235**	0.231**	0.276**	0.319***	0.254**	0.258**
	(0.118)	(0.112)	(0.119)	(0.112)	(0.121)	(0.112)	(0.120)	(0.112)
Concentration	−4.016**	17.234*	−4.039**	15.024	−2.286	12.314	−4.083**	15.831*
	(1.955)	(9.013)	(1.924)	(9.515)	(1.949)	(7.484)	(1.951)	(9.313)
Information sharing	3.437***	18.697***	3.412***	17.255**	3.087***	14.591**	3.252***	17.742**
	(1.223)	(6.918)	(1.144)	(7.281)	(1.154)	(6.240)	(1.139)	(7.129)
Information sharing x Concentration		−26.716**		−24.110**		−20.140**		−25.118**
		(11.421)		(12.028)		(10.085)		(11.785)
Governance			0.590	0.013	1.864**	1.795*	1.054*	0.625
			(0.568)	(0.628)	(0.811)	(0.948)	(0.619)	(0.638)
Constant	12.512***	1.993	13.355***	3.526	14.145***	9.343	14.051***	3.584
	(4.786)	(6.284)	(4.858)	(6.871)	(4.774)	(6.263)	(4.828)	(6.670)
No. of observations	1402	1402	1402	1402	1402	1402	1402	1402
Hansen test p-value	0.162	0.430	0.193	0.412	0.269	0.532	0.156	0.430
Resid. AR(2) test p-value	0.862	0.795	0.876	0.800	0.910	0.842	0.881	0.809

This table shows the dynamic system GMM estimation results for the effect of credit information on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4 Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses.

* Indicates significance at 10%.

** Indicates significance at 5%.

*** Indicates significance at 1%.

Table 10: Endogenous depth of credit information, concentration and bank lending: dynamic two-step system GMM estimation

Dependent variable: Lending

	Governance indicator							
	None		*Rule of law*		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lending_{-1}	0.777***	0.822***	0.752***	0.874***	0.748***	0.883***	0.743***	0.892***
	(0.052)	(0.048)	(0.052)	(0.055)	(0.052)	(0.076)	(0.054)	(0.078)
Profitability	0.380***	0.367***	0.386***	0.506**	0.356***	0.500**	0.342***	0.526**
	(0.117)	(0.105)	(0.116)	(0.241)	(0.109)	(0.242)	(0.121)	(0.248)
Deposit mix	−0.032*	−0.030*	−0.040**	−0.017	−0.040**	−0.013	−0.041**	−0.012
	(0.019)	(0.018)	(0.018)	(0.017)	(0.018)	(0.019)	(0.018)	(0.019)
Government share	−0.018	−0.015	−0.017	−0.010	−0.016	−0.010	−0.018	−0.009
	(0.011)	(0.009)	(0.011)	(0.008)	(0.011)	(0.009)	(0.011)	(0.008)
Inflation	−0.229***	−0.177***	−0.241***	−0.162***	−0.234***	−0.149**	−0.240***	−0.144**
	(0.063)	(0.056)	(0.060)	(0.049)	(0.061)	(0.062)	(0.061)	(0.061)
GDP growth	0.371***	0.310***	0.379***	0.308***	0.390***	0.334***	0.399***	0.345***
	(0.132)	(0.118)	(0.134)	(0.118)	(0.131)	(0.123)	(0.133)	(0.128)
Concentration	−0.495	9.314	−1.397	13.241*	−0.390	13.026**	−1.252	15.073**
	(1.927)	(6.287)	(1.934)	(7.058)	(1.932)	(6.552)	(1.960)	(7.514)
Depth of information	0.921***	3.316**	0.995***	4.019**	0.850***	4.005**	0.961***	4.372**
	(0.274)	(1.679)	(0.303)	(1.915)	(0.319)	(1.803)	(0.308)	(1.994)
Depth of information x Concentration		−5.463*		−6.813*		−6.847**		−7.633**
		(3.166)		(3.561)		(3.321)		(3.774)
Governance			0.083	−0.840	1.235	−0.481	0.602	−0.328
			(0.647)	(0.579)	(0.994)	(0.791)	(0.737)	(0.596)
Constant	11.470***	4.145	13.793***	−2.587	14.105***	−3.078	14.557***	−4.868
	(4.249)	(4.726)	(4.259)	(4.583)	(4.259)	(6.006)	(4.519)	(6.547)
No. of observations	1402	1402	1402	1402	1402	1402	1402	1402
Hansen test p-value	0.182	0.475	0.324	0.461	0.358	0.249	0.192	0.261
Resid. AR(2) test p-value	0.977	0.898	0.973	0.912	0.997	0.927	0.988	0.925

This table shows the dynamic system GMM estimation results for the effect of credit information on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4 Robust Windmeijer (2005) finite-sample corrected standard errors are in parentheses.
* Indicates significance at 10%.
** Indicates significance at 5%.
*** Indicates significance at 1%.

Table 11: Credit information, concentration and bank lending: pooled OLS estimation

Dependent variable: Lending

	Governance indicator							
	None		*Rule of law*		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lending_{-1}	0.822***	0.821***	0.822***	0.822***	0.819***	0.819***	0.821***	0.820***
	(0.023)	(0.023)	(0.022)	(0.023)	(0.022)	(0.022)	(0.022)	(0.022)
Profitability	0.171**	0.163*	0.171**	0.163*	0.165*	0.160*	0.168**	0.161*
	(0.083)	(0.085)	(0.083)	(0.085)	(0.084)	(0.086)	(0.082)	(0.084)
Deposit mix	−0.036**	−0.035**	−0.036**	−0.035**	−0.036**	−0.035**	−0.036**	−0.035**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Government share	−0.011	−0.011	−0.011	−0.011	−0.010	−0.011	−0.011	−0.011
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
Inflation	−0.130**	−0.140**	−0.131**	−0.143**	−0.128*	−0.136**	−0.127*	−0.137**
	(0.062)	(0.060)	(0.060)	(0.057)	(0.065)	(0.063)	(0.064)	(0.061)
GDP growth	0.046	0.063	0.045	0.059	0.069	0.081	0.057	0.071
	(0.073)	(0.075)	(0.080)	(0.080)	(0.075)	(0.075)	(0.079)	(0.079)
Concentration	−2.185	2.838	−2.218	3.014	−1.181	3.009	−2.122	2.690
	(1.894)	(2.787)	(1.937)	(2.787)	(2.321)	(2.646)	(1.991)	(2.677)
Information sharing	1.790*	5.267**	1.803*	5.494**	1.511	4.536*	1.735*	5.087*
	(1.029)	(2.520)	(0.993)	(2.431)	(0.980)	(2.440)	(1.023)	(2.547)
Information sharing x Concentration		−6.198*		−6.537*		−5.328		−5.955*
		(3.356)		(3.332)		(3.318)		(3.412)
Governance			−0.069	−0.202	0.918	0.801	0.347	0.273
			(0.672)	(0.629)	(0.788)	(0.745)	(0.650)	(0.602)
Constant	12.798***	9.867***	12.792***	9.691***	12.703***	10.195***	12.924***	10.082***
	(2.139)	(2.943)	(2.130)	(2.876)	(2.086)	(2.652)	(1.987)	(2.748)
No. of observations	1421	1421	1421	1421	1421	1421	1421	1421
Adj. R^2	0.799	0.800	0.799	0.799	0.800	0.800	0.799	0.799

This table shows the OLS estimation results for the effect of credit information on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4. Heteroskedasticity-robust standard errors, corrected for clustering at the country level, are in parentheses.
* Indicates significance at 10%.
** Indicates significance at 5%.
*** Indicates significance at 1%.

Table 12: Depth of credit information, concentration and bank lending: pooled OLS estimation

Dependent variable: Lending

	Governance indicator							
	None		*Rule of law*		*Regulatory quality*		*Control of corruption*	
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Lending_{-1}	0.824***	0.823***	0.825***	0.824***	0.822***	0.821***	0.824***	0.822***
	(0.021)	(0.022)	(0.021)	(0.022)	(0.021)	(0.021)	(0.021)	(0.021)
Profitability	0.152*	0.138	0.151*	0.138	0.150*	0.137	0.152*	0.138
	(0.086)	(0.088)	(0.086)	(0.088)	(0.087)	(0.089)	(0.085)	(0.087)
Deposit mix	−0.036**	−0.034**	−0.036**	−0.035**	−0.036**	−0.034**	−0.036**	−0.034**
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Government share	−0.011	−0.012	−0.011	−0.012	−0.011	−0.011	−0.011	−0.012
	(0.009)	(0.009)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Inflation	−0.161**	−0.165**	−0.167***	−0.171***	−0.156**	−0.160**	−0.161**	−0.164***
	(0.062)	(0.061)	(0.056)	(0.054)	(0.065)	(0.062)	(0.060)	(0.059)
GDP growth	0.051	0.087	0.044	0.079	0.065	0.097	0.052	0.089
	(0.074)	(0.072)	(0.081)	(0.079)	(0.074)	(0.072)	(0.080)	(0.077)
Concentration	−0.585	3.838*	−0.634	3.852*	−0.149	4.054*	−0.587	3.842*
	(1.778)	(1.985)	(1.764)	(2.006)	(2.158)	(2.125)	(1.693)	(2.005)
Depth of information	0.418**	1.556***	0.457**	1.616***	0.346*	1.458***	0.417*	1.553***
	(0.199)	(0.454)	(0.182)	(0.430)	(0.202)	(0.469)	(0.211)	(0.459)
Depth of information x Concentration		−2.257***		−2.292***		−2.183***		−2.266***
		(0.749)		(0.705)		(0.788)		(0.760)
Governance			−0.388	−0.426	0.643	0.532	0.010	0.073
			(0.656)	(0.599)	(0.885)	(0.807)	(0.683)	(0.611)
Constant	12.773***	10.076***	12.644***	9.894***	12.867***	10.243***	12.779***	10.114***
	(2.233)	(2.233)	(2.181)	(2.220)	(2.107)	(2.024)	(1.962)	(2.038)
No. of observations	1421	1421	1421	1421	1421	1421	1421	1421
Adj. R^2	0.800	0.800	0.799	0.800	0.800	0.800	0.799	0.800

This table shows the OLS estimation results for the effect of credit information sharing on bank lending. Time fixed dummies are included in all estimations. All variables are as described in Table 1 and Subsection 5.4. Heteroskedasticity-robust standard errors, corrected for clustering at the country level, are in parentheses.

* Indicates significance at 10%.

** Indicates significance at 5%.

*** Indicates significance at 1%.

Table A.1: Sample number of banks by country

Country	**No. of banks**	**Country**	**No. of banks**
Algeria	16	Mauritius	13
Angola	12	Morocco	18
Benin	7	Mozambique	10
Botswana	11	Namibia	9
Burkina Faso	7	Niger	4
Cameroon	12	Nigeria	13
Congo, D.R. of	9	Senegal	10
Cote D'ivoire	9	Seychelles	5
Egypt	30	Sierra Leone	8
Ethiopia	9	South Africa	42
Gabon	5	Sudan	20
Gambia	4	Swaziland	5
Ghana	20	Tanzania	26
Kenya	34	Togo	7
Madagascar	5	Tunisia	34
Malawi	10	Uganda	16
Mali	8	Zambia	16
Mauritania	7		

Source: Fitch-IBCA's Bankscope database and own calculation.