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Why Do African Banks Lend so Little?[¶]

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Abstract. We put forward a plausible explanation of African financial under-development in the form of a bad credit market equilibrium. Utilising an appropriately modified IO model of banking, we show that the root of the problem could be unchecked moral hazard (strategic loan defaults) or adverse selection (a lack of good projects). Applying a dynamic panel estimator to a large sample of African banks, we show that loan defaults are a major factor inhibiting bank lending when the quality of regulation is poor. We also find that once a threshold level of regulatory quality has been reached, improvements in the default rate or regulatory quality do not matter, providing support for our theoretical predictions.

Keywords: Dynamic panel data, African financial under-development, African credit markets

JEL: G21, O16

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1 Introduction

Africa remains today one of the most financially under-developed parts of the world. Financial under-development is frequently associated with a country's inability to mobilise sufficient amounts of saving to satisfy the demand for credit. A recent study by the World Bank has, however, shown that African banking systems, although lacking in depth compared to other regions in the world, are excessively liquid (Honohan and Beck 2007). That is to say, savings mobilisation does not appear to represent a binding constraint on African banks' ability to lend. Instead, African banks complain of a lack of credit worthy borrowers while at the same time households and firms complain about lack of credit. The same study shows that the least developed banking systems in Africa are also the most liquid, which implies that resolving the paradox of excess liquidity may hold the key to understanding African financial under-development. To do so requires focussing on the structure and mechanics of African credit markets.

The main contribution of this paper is to put forward a plausible explanation of African financial under-development in the form of a bad credit market equilibrium. We show that the root of the problem could be either moral hazard—taking the form of strategic loan defaults—or adverse selection emanating from the lack of good projects. Theoretically, the two are almost indistinguishable but we make an attempt to gauge empirically which of the two is the most likely cause.

The first part of the paper is theoretical. It modifies a standard IO model of banking to analyse the market for bank credit. The model encapsulates various stylised facts of African credit markets, including high loan default rates. In the model, sub-optimal equilibria arise when there are severe informational imperfections and institutions intended to contain moral hazard are weak. In these sub-optimal equilibria, the loan default rate (an endogenous variable in the model) is high, which deters the expansion of bank credit. When we use the model to explore the impact of improvements in institutions designed to mitigate informational imperfections, we find important non-linearities in the response of the banking system. For example, improvements in contract enforcement can reduce the impact of loan default on lending, but *only* when enforcement is low to begin with. Once the quality of contract enforcement has reached a certain level, further improvements will have no impact on banks' behaviour. These results appear in both the moral hazard and adverse selection versions of the model, and are consistent with the threshold effects implicit in other macroeconomic studies.

The second part of the paper is empirical. It is aimed at testing various specific predictions of the theory utilising panel data for hundreds of African banks over a ten year period. Specifically, it explores the relationship between the amount that African banks are willing to lend, loan default rates and the institutional environment, allowing for threshold effects.[1] The model is fitted using a GMM dynamic panel estimator (Arellano and Bond 1991, Blundell and Bond 1998). Our empirical results provide strong support for the predictions of our theoretical model, and we are able to identify a threshold effect in regulatory quality. Moreover, they pass a variety of robustness checks, including sensitivity to different values of the threshold level as well as alternative dynamic panel data estimators. Finally, we provide some evidence on whether the root cause of financial under-development lies in strategic loan default (moral hazard) or the lack of good projects (adverse selection).

Our paper complements a growing literature on African financial systems that is mainly macroeconomic in approach. Honohan and Beck (2007) provide the starting point for our paper in the sense that we delve further into some of the issues they raise in their important World Bank study. More recently, Allen, Otchere and Senbetm (2010) provide a comprehensive, thorough and up-to-date overview of African financial systems, including banks, financial markets and microfinance. Their survey confirms the dominance of traditional banking over other forms of formal finance, particularly in Sub-Saharan Africa. It also highlights the tendency of African banks to invest in government securities but does not address the factors that explain excess liquidity. Other studies explore the links between financial development and economic growth in Africa. Gries, Kraft and Meierrieks (2009),

[1] Unlike the bulk of the literature on African financial systems that is mainly macroeconomic, our study uses microeconomic data, allowing to search for threshold effects more directly.

for example, find limited support to the finance-led growth hypothesis in 16 Sub-Saharan African countries. Earlier work on a broader range of developing countries by Demetriades and Law (2006) shows that this is predominantly a feature of low income countries, most of which are, in fact, located in Sub-Saharan Africa. In middle income countries, some of which are located in North Africa, the link between finance and growth is much stronger.[2] Similar threshold effects in the finance-growth relationship have also been documented by Rioja and Valev (2004). Such macroeconomic effects are consistent with our own findings of threshold effects in bank credit that are derived from a micro-setting.

The paper is structured as follows. Section 2 sets out the theoretical model and describes various credit market equilibria under moral hazard and adverse selection. Section 3 outlines the empirical model, describes the data set and explains the estimation method. Section 4 presents the empirical results. Section 5 summarises and concludes.

2 Theory

One of the most important features of African credit markets is that credit registries are either completely absent or are in their infancy. The absence of credit registries makes screening loan applicants extremely challenging. Combined with weak contract enforcement—another stylised feature of many African economies—this encourages loan default. As we will see later, variation in regulatory quality across countries and over time is particularly large in Africa. In this environment, it is no surprise to observe that banks in countries with weak regulatory institutions are cautious in extending loans and that the default rate is very high. In the absence of systematic credit history records, default does not have any impact on credit ratings, and the cost of default to borrowers is relatively low. In these circumstances, credit markets are prone to an extreme moral hazard problem in the form of strategic loan defaults: some loan applicants may apply for loans with no intention of

[2]Demetriades and Law (2006) provide evidence which suggests that in low income countries institutional quality is a more robust driver of long run growth than financial depth.

ever repaying them. Equally, the difficulty of distinguishing successful entrepreneurs from unsuccessful ones can create an adverse selection effect. Our theoretical model adds to the existing literature on moral hazard and loan default by exploring in detail how the extent of contract enforceability and the extent of moral hazard combine to determine the type of equilibrium prevailing in the loans market. This provides the basis for our empirical model of bank behaviour in African countries with widely varying levels of regulatory quality.

2.1 Benchmark model of strategic default with identical banks

Our starting point is the "circular city" model of product differentiation applied to the lending side of banking.[3] n private identical banks compete for loan contracts. The fixed cost of setting up a bank is F and there are no entry restrictions. Bank i ($i = 1, ..., n$) maximises its payoff by setting the lending rate, r_i, for all its loan applications. Loan applicants are entrepreneurs that have access to an identical and riskless investment technology, which gives return R on one unit of invested funds. Entrepreneurs (henceforth, borrowers) can be either opportunistic, with probability γ ($0 < \gamma < 1$), or honest, with probability $1 - \gamma$. The borrower's type is private information, while the probabilities are common knowledge. An honest borrower repays his loan without fail, while an opportunistic borrower may choose to either repay or default on his loan, depending on the extent of loan contract enforcement. If a borrower defaults on his loan, the bank gets compensation $d > 0$ with probability λ (otherwise, with probability $1 - \lambda$, the bank gets 0). The banks have access to the following screening technology: when it screens a loan application, the bank finds that the applicant is opportunistic with probability σ ($0 < \sigma < 1$), otherwise, with

[3] The model was originally developed by Salop (1979); see also a useful discussion in relation to bank deposit contracts in Freixas and Rochet (1997). Andrianova, Demetriades and Shortland (2008) extend it to analyse depositor behaviour in the presence of opportunistic banks and government owned banks. It is particularly relevant in the African context where product differentiation can be thought of as representing a bank's ethno-linguistic characteristics.

probability $1-\sigma$, the bank has no information as to the type of the applicant.[4] The bank may choose to use its screening technology and, having screened all applicants, the bank can also choose whether to refuse (or not) applications of those borrowers who were flagged up by screening as opportunistic.[5] Borrowers are uniformly distributed along a circle of a unitary length.[6] A borrower incurs a positive transportation cost t which is proportional to the distance between the depositor and the bank. Every borrower can apply for a loan to at most one bank. All players are risk-neutral. Every bank has sufficient funds to approve all of its applications if deemed profitable.[7]

The timing of the game is as follows.

(1) Banks decide whether to enter; n banks enter.

(2) Bank i ($i = 1, \ldots, n$) sets its lending rate r_i.

(3) Each borrower chooses the bank in which to apply for a loan of 1 monetary unit.

(4) Facing the demand for loans, D_i, bank i ($i = 1, \ldots, n$) chooses whether to screen or not all of its loan applications.

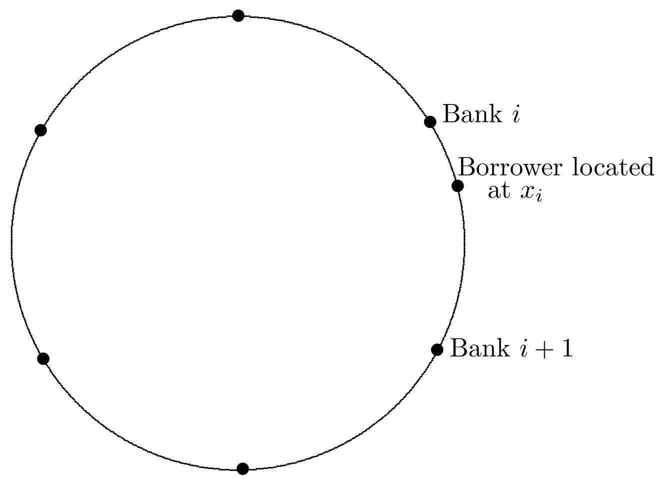
[4]We justify this assumption by alluding to a repeated game frame in the background: if a borrower defaulted on his loan in the past, there may be a record of the default that the bank could learn about through screening. Honest borrowers don't have such record, while opportunistic borrowers may or may not have such record, depending on their past actions. Note that banks cannot share information about borrowers. The process by which African banks make decisions about individual customers is typically very opaque, and not documented, so we have no way of modelling information sharing empirically.

[5]We do not allow the bank to charge a different rate for borrowers with a "stained" credit record. Once the lending rate is posted in order to attract loan applications, the bank cannot decide to charge a higher rate for borrowers with a poor credit record, but only to refuse credit at the posted rate, which we believe is plausible.

[6]For simplicity, let us assume that the distribution density is 1.

[7]Obviously, this is a simplification but not an unreasonable one in the light of Honohan and Beck (2007).

Figure 1: *Structure of the banking industry*



(5) Bank i chooses which applications to approve and which to decline.

(6) A borrower with an approved loan invests his 1 monetary unit and obtains return R.

(7) An honest borrower repays his loan, an opportunistic borrower chooses whether to repay or default on his loan.

(8) If any of its loans are defaulted on, the bank seeks compensation.

(9) Payoffs are realized.

2.2 Solution in the benchmark

Given the sequential nature of the game, the appropriate solution method is backward induction. Let $q \in \{0, 1\}$ represent an opportunistic borrower's decision to repay his loan contract where the value of q ($q = 1$ repay, or $q = 0$ default) is set by an opportunistic borrower to maximize his expected payoff. Let $\xi \in \{0, 1\}$ denote a bank's decision to screen ($\xi = 1$ is screen, $\xi = 0$ is no screen).[8] And let $p \in \{0,\ 1\}$ denote a bank's decision to approve all its applications when it decides not to screen.[9] The expected payoffs of the players (borrowers and banks) are calculated as follows. By going to bank i, an honest borrower located at distance x_i expects to obtain:

$$U_i^{1-\gamma} = [\xi + (1-\xi)p][R - r_i] - tx_i \tag{1}$$

By applying to bank i, an opportunistic borrower located at distance x_i from the bank expects to obtain

$$U_i^{\gamma} = [\xi(1-\sigma) + (1-\xi)p][q(R - r_i) + (1-q)(1-\lambda)d] - tx_i \tag{2}$$

A bank's expected payoff depends on its choice of actions: screen and finance those with apparently clean record, or don't screen and then either finance all loan applications or finance none. Thus bank i's payoff is written as follows:

$$\begin{aligned} V_i \;=\; & D_i\Big[\xi\Big\{(1+r_i)\Big((1-\gamma)+\gamma(1-\sigma)q\Big) + (1+r_0)\gamma\sigma + \gamma(1-q)(1-\sigma)\lambda d\Big\} + \\ & +(1-\xi)\Big\{p(1+r_i)\Big((1-\gamma)+\gamma q\Big) + p\gamma(1-q)\lambda d + (1-p)(1+r_0)\Big\}\Big] \end{aligned} \tag{3}$$

Assumptions we need to have in place here are the following.

Assumption 1 $$tF^2 > (1+r_0)^2 \tag{A1}$$

(A1) ensures that in the absence of enforcement problems, lending to entrepreneurs is sufficiently profitable (ie it must pay off more than the opportunity cost). We could also think of this assumption as ensuring a "sufficient degree of product differentiation", since t captures the degree of product differentiation in the model of bank competition.

[8] As all banks are identical for now, the subscript i is dropped in the notation for probabilities associated with the banks' decision-making.

[9] This economises on notation somewhat, as it can be checked that a bank's strategy (screen, finance all) is dominated by (don't screen, finance all), for a non-negative screening cost.

Assumption 2 $$R \geq \frac{3}{2}\sqrt{Ft} - 1 \tag{A2}$$

(A2) is simply a participation constraint of the marginal borrower in the absence of enforcement problems (ie it ensures a non-negative ex ante expected payoff).

Four types of pure strategy equilibria emerge in this game (see Table 1): "high" equilibrium (HE) where all borrowers repay and banks approve all loan application without resorting to screening, upper intermediate equilibrium (IE1) whereby despite opportunistic borrowers' default the banks find it profitable to lend to all applicants and avoid screening, lower intermediate equilibrium (IE2) whereby opportunistic borrowers default, banks screen and finance those whose credit record is apparently clean, and finally "low" equilibrium (LE) in which there is no lending at all (banks put their loanable funds into the safe asset).

TABLE 1: *Description of equilibria.*

Equilibrium		*Equilibrium behaviour*	
High	*(HE)*	$q = 1$ (no default)	$\xi = 0,\ p = 1$ (no screen, finance all)
Upper Intermediate	*(IE1)*	$q = 0$ (default)	$\xi = 0,\ p = 1$ (no screen, finance all)
Lower Intermediate	*(IE2)*	$q = 0$ (default)	$\xi = 1$ (screen, finance some)
Low	*(LE)*	$q = 0$ (default)	$\xi = 0,\ p = 0$ (no screen, no finance)

Proposition 1 *Assume (A1) and (A2). A unique (pure strategy) equilibrium exists and it is of type:*

(i) HE, if $\lambda \geq \bar{\lambda}$. Then $r_i = \sqrt{Ft} - 1$ and $n = \sqrt{t/F}$;

(ii) IE1, if $\underline{\lambda} \leq \lambda < \bar{\lambda}$*. Then* $r_i = \sqrt{Ft/(1-\gamma)} - 1 - \frac{\gamma}{1-\gamma}\lambda d$ *and* $n = \sqrt{t(1-\gamma)/F}$*;*

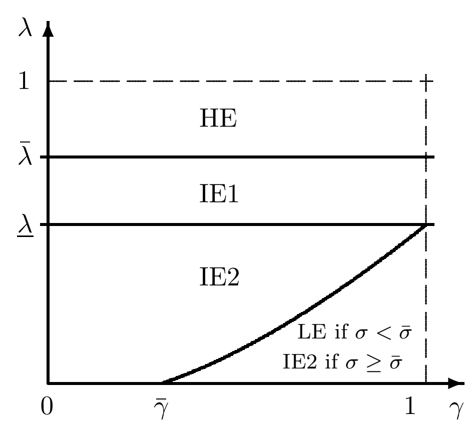
(iii) IE2, if $\lambda < \underline{\lambda}$*, and either* $\gamma \leq \bar{\gamma}$*, or* $\gamma > \bar{\gamma}$ *together with* $\sigma > \bar{\sigma}$*. Then* $r_i = \sqrt{Ft/(1-\gamma)} - 1 - \frac{\gamma}{1-\gamma}[(1-\sigma)\lambda d + \sigma(1+r_0)]$ *and* $n = \sqrt{t(1-\gamma)/F}$*;*

(iv) LE, if $\lambda < \underline{\lambda}$*,* $\gamma > \bar{\gamma}$ *and* $\sigma \leq \bar{\sigma}$*. Then* $n = D(1+r_0)/F$*;*

where $i = 1, \ldots, n$*,* $\underline{\lambda} = (1+r_0)/d$*,* $\bar{\lambda} = (1+r_i)/d$*,* $\bar{\gamma} = (r_i - r_0)/(1 + r_i - \lambda d)$ *and* $\bar{\sigma} = 1 - [(1-\gamma)/\gamma][(r_i - r_0)/(1 + r_0 - \lambda d)]$.

Figure 2 provides a graphic representation of the results contained in Prop. 1.

FIGURE 2: *Equilibria in the benchmark*



2.3 When banks' screening technologies differ

We now allow banks to differ in their ability to screen: more established banks may well have an informational advantage over a "new" bank. Formally and simply, let there be two types of banks: the α-type is the bank that has a screening technology as described in the benchmark section (finds out about an existing stained credit record with probability σ), and the β-type is the bank that has a useless screening technology (learns nothing even if it screens). The proportion of each type of bank (α and β, respectively, with $\alpha + \beta = 1$) is publicly known, but the type itself is private information. Adapting the notation from the earlier section: ξ is α-bank decision to screen, and p_k is k's bank decision to lend when not screening ($k = \{\alpha,\ \beta\}$).

The expected payoffs change to:

$$U_i^{1-\gamma} = \Big[\alpha\Big(\xi + (1-\xi)p_\alpha\Big) + (1-\alpha)p_\beta\Big][R - r_i] - tx_i \tag{4}$$

$$U_i^{\gamma} = \Big[\alpha\Big(\xi(1-\sigma) + (1-\xi)p_\alpha\Big) + (1-\alpha)p_\beta\Big]\Big[1 + R - q(1+r_i) - (1-q)\lambda d\Big] - tx_i \tag{5}$$

$$\begin{aligned} V_i^{\alpha} = {} & D_i\Big[\xi\Big\{(1+r_i)\Big((1-\gamma) + \gamma(1-\sigma)q\Big) + (1+r_0)\gamma\sigma + \gamma(1-q)(1-\sigma)\lambda d\Big\} + \\ & +(1-\xi)\Big\{p_\alpha(1+r_i)\Big((1-\gamma) + \gamma q\Big) + p_\alpha\gamma(1-q)\lambda d + (1-p_\alpha)(1+r_0)\Big\}\Big] \end{aligned} \tag{6}$$

$$V_i^{\beta} = D_i\Big[p_\beta(1+r_i)\Big((1-\gamma) + \gamma q\Big) + p_\beta\gamma(1-q)\lambda d + (1-p_\beta)(1+r_0)\Big] \tag{7}$$

Notice that the equilibria without screening are not affected by this modification in the assumption on banks' screening technologies. In a pooling equilibrium with screening (IE2), β-type bank is mimicking the α-type, by setting the loan approval probability to be equal to $p_\beta = 1 - \sigma\gamma$. The less efficient at screening bank can do so, although the pool of the approved loans for this bank is obviously going to be worse than that of the more efficient at screening bank. The parameter range in which each of the four possible equilibria obtain does not change, while the equilibrium values of n and r_i in IE2 now become

$$
\begin{aligned}
n &= \sqrt{\frac{t(1-\gamma)}{F\Big(1-\sigma\gamma(1-\alpha)\Big)}} && (8)\\
r_i &= \frac{t}{n}\frac{1}{1-\sigma\gamma(1-\alpha)} - 1 - \frac{(1+r_0)\sigma\gamma + \gamma(1-\sigma)\lambda d}{1-\gamma} && (9)
\end{aligned}
$$

Compared to the benchmark case of section 2.2, the equilibrium lending rate and the number of banks that enter are both larger when the screening technology differs across banks.

2.4 Re-interpreting the benchmark as a pure adverse selection model

This section considers the possibility that the default on a loan may be due to reasons other than the strategic behaviour of a borrower. Suppose now that a borrower defaults because the project for which he obtained the loan has turned out to be a bad project with an ex post zero return. Now the parameter γ captures the proportion of borrowers whose projects are worthless (have zero realized return). The type of the project determines the type of the borrower and is borrower's private knowledge, although the value of γ is publicly known. As the loan is sunk in the zero-return project, the lender expects to get the liquidation value of the project, $0 < d < 1$, with probability λ. The screening technology of the bank allows it to filter out "bad" projects from being financed. A zero-return project is found out by the screening technology with probability σ (similar to the benchmark case). As in section 2.2, all banks here possess the same screening technology.

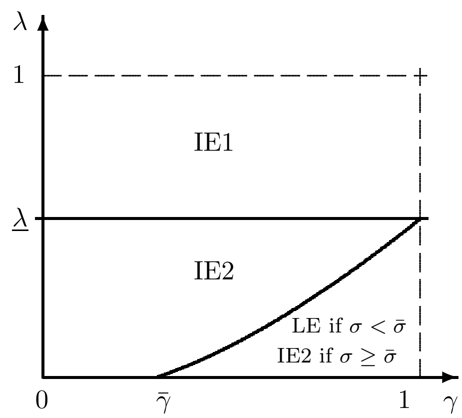
The expected payoffs change to:

$$U_i^{1-\gamma} = \Big[\xi + (1-\xi)p\Big][R - r_i] - tx_i \tag{10}$$

$$U_i^{\gamma} = \Big[\xi(1-\sigma) + (1-\xi)p\Big](1-\lambda d) - tx_i \tag{11}$$

$$\begin{aligned} V_i = \; & D_i\Big[\xi\Big\{(1+r_i)(1-\gamma) + (1+r_0)\gamma\sigma + \gamma(1-\sigma)\lambda d\Big\} + \\ & +(1-\xi)\Big\{p(1+r_i)(1-\gamma) + p\gamma\lambda d + (1-p)(1+r_0)\Big\}\Big] \end{aligned} \tag{12}$$

FIGURE 3: *Equilibria in pure adverse selection model*



It is straightforward to establish that the same types of equilibria obtain in this pure adverse selection version of the model as in the benchmark case, with one exception: the parameter space that previously housed IE1 and HE equilibria in the benchmark case, now only allows IE1. The qualitative results are therefore independent of whether the model is interpreted as a strategic default setting (where some borrowers may choose to default depending on the extent of loan contract enforcement) or pure adverse selection setting (where loans made to bad projects will be defaulted on with certainty).[10]

[10]This agrees with the result in Milgrom (1987) on the equivalence of adverse selection and moral hazard

2.5 "Bad luck" setup without strategic default

Suppose now that instead of knowing their type before applying for a loan, borrowers learn the type of their project—"good" project with return $R > 1$ or "bad" project with zero return—only after making the investment. In other words, all borrowers are subject to a bad shock (e.g. because the economy is doing worse than expected, etc) and screening entrepreneurs/projects ex ante of loan approval is not possible (not informative). Assume additionally that when investment returns are realized, it is costless for a lender to establish the realized return (state falsification is not possible). Then, choosing between approving all loans or approving none, bank i compares the following two payoffs: $D_i(1-\gamma)(1+r_i)$ and $D_i(1+r_0)$. Approving all loans results in a higher payoff when $\gamma < (r_i - r_0)/(1+r_i)$, which is similar to the threshold value $\bar{\gamma}$ obtained earlier in the benchmark case (to be precise, it is exactly the same as with pure bad luck and absent any collateral, $d = 0$). Thus, the only two possible equilibria here are IE1 and LE, in the notation of the benchmark section (but note that IE1 replaces IE2 here because screening is not feasible in the current setting). And the equilibrium is determined by the parameter γ.

3 Empirical Strategy, Data and Econometric Methods

The theoretical model indicates that a bank's willingness to make new loans depends on the proportion of opportunistic borrowers (or the proportion of low-productivity borrowers) that it faces and on the extent of contract enforcement in the market in which it operates.

representations of asymmetric information.

Overall, bank lending is increasing in the extent of contract enforcement and decreasing in the proportion of opportunistic borrowers, but these effects are not linear in the following sense. For a given punishment technology facing a bank (a given d), the proportion of opportunistic borrowers matters only when the extent of contract enforcement is below a certain threshold level. Moreover, within this range, a small change in the extent of contract enforcement has no effect on bank behaviour. However, the threshold level will depend on the characteristics of each loan contract; for example, an increase in the parameter d will lower the threshold. These characteristics are not directly observable (at least in our data set). If they vary across contracts, then for a given proportion of opportunistic borrowers, a small change in the extent of contract enforcement can affect the volume of loans, if the change represents a crossing of the threshold for some group of contracts. By the same token, a small difference in the extent of contract enforcement can affect the impact on loans of a change in the proportion of opportunistic or low-productivity borrowers. Nevertheless, there will be an overall threshold level of the extent of contract enforcement corresponding to the threshold for the most extreme set of technology parameters. Above this level, neither improvements in contract enforcement nor changes in the proportion of opportunistic or low-productivity borrowers have any effect on loan volumes.[11]

[11] The model also suggests that there is a region in which banks will not lend at all. This is a rather extreme situation which we do not expect to arise frequently in practice hence it may not lend itself to econometric testing due to insufficient observations. In our dataset, there are 85 observations for which the loans-to-assets ratio is zero. The average regulatory quality is –0.27 while information on the default rate is missing.

These observations suggest the following empirical model for the volume of loans:

$$\begin{aligned} LA_{jt} &= \alpha^0 + \theta \cdot DF_{jt} + \delta \cdot RQ_{jt} + \eta \cdot DF_{jt} \cdot RQ_{jt} \quad | \quad RQ_{jt} < RQ^* \\ LA_{jt} &= \alpha^1 \quad | \quad RQ_{jt} \geq RQ^* \end{aligned} \tag{13}$$

where LA_{jt} is the volume of loans made by the jth bank in period t (expressed as a fraction of bank assets),[12] DF_{jt} is the default rate it faces and RQ_{jt} is the quality of the regulatory environment in which it operates, which determines the extent of contract enforcement. RQ^* is some overall threshold level of RQ_{jt}. Greek letters represent parameters. In the empirical application, we estimate the first version of the model for both low and high regulatory quality values, separately, and test the restriction of zero coefficients (θ, δ and η).

It is likely that we will also observe systematic variations in the volume of loans over time (α_t) and across banks (β_j). (β_j controls for variation in fixed characteristics of banks that may affect their access to screening technology, and variation in fixed characteristics of the market in which they operate, such as country size.) There will also be completely random variations in the volume of loans (u_{jt}), because of unobservable shocks in the costs that banks face. Perhaps there is also some persistence in the effect of shocks. In this case, our model will be:

$$LA_{jt} = \alpha_t^0 + \beta_j^0 + \rho^0 \cdot LA_{jt-1} + \theta \cdot DF_{jt} + \delta \cdot RQ_{jt} +$$

[12] In Section 2, we assumed that the volume of bank assets remains fixed, a simplification which makes the theoretical model more tractable; the theory does not explain variation in bank size. Normalization on the volume of assets controls for this variation. Demetriades and Fielding (2010) explore the determinants of bank assets in West Africa.

$$+\eta \cdot DF_{jt} \cdot RQ_{jt} + u^0_{jt} \quad | \quad RQ_{jt} < RQ^*$$

$$LA_{jt} = \alpha^1_t + \beta^1_j + \rho^1 \cdot LA_{jt-1} + u^1_{jt} \quad | \quad RQ_{jt} \geq RQ^* \tag{14}$$

Relevant annual panel data on individual African banks are available in Bank Scope for 1999–2008. However, for many banks observations of some variables are missing, so our sample is limited to 378 banks in total.[13] There is little information on the factors that are likely to drive idiosyncratic variations in banks' costs. However, one factor that we can control for is the government's share in the ownership of a bank (GV_{jt}). The political constraints facing a publicly owned bank may force it to lend more than a private bank. For a given default rate, this effect is likely to be mopped up by the bank-specific fixed effect β_j, because ownership shares change very infrequently in our sample. However, if government banks are relatively insensitive to loan default rates, then one final modification of equation (14) is necessary:

$$\begin{aligned} LA_{jt} &= \alpha^0_t + \beta^0_j + \rho^0 \cdot LA_{jt-1} + \theta \cdot DF_{jt} + \zeta \cdot DF_{jt} \cdot GV_{jt} + \delta \cdot RQ_{jt} + \\ &\quad +\eta \cdot DF_{jt} RQ_{jt} + u^0_{jt} \mid RQ_{jt} < RQ^* \\ LA_{jt} &= \alpha^1_t + \beta^1_j + \rho^1 \cdot LA_{jt-1} + u^1_{jt} \quad | \quad RQ_{jt} \geq RQ^* \end{aligned} \tag{15}$$

LA_{jt} is measured as the ratio of total loans by each bank, as indicated in Bank Scope, expressed as a fraction of its total assets. DF_{jt} is measured as the ratio of impaired loans to total loans. It should be noted that DF_{jt} does not measure exactly the same quantity as the parameter γ in the theoretical model: γ captures the fraction of borrowers with the potential to default, not the actual fraction of borrowers who do default. Unlike γ, DF_{jt}

[13]Appendix B lists the countries in the dataset, and the number of banks in each country.

is likely to be endogenous to bank behaviour: for example, it is likely to depend partly on the efficiency with which loan applicants are screened. Consistent estimation of equation (15) will therefore require the use of some set of instrumental variables, as discussed below.

RQ_{jt} is measured by the *Regulatory Quality* index for the country in which the bank operates, as reported in the Worldwide Governance Indicators (Kaufmann, Kraay and Mastruzzi 2009). Like all the other Governance Database indices, *Regulatory Quality* is normalised so that the average world value in the base year is zero and the corresponding standard deviation is unity.[14]

Tables 2 and 3 provide summary statistics of all the variables, including a correlation matrix. The mean of the loans to assets ratio is 50%, which is low by international standards, confirming the problem highlighted by the World Bank. This variable displays substantial variation, ranging from a minimum value of 2% to a maximum value of 98%. The default rate is also very high by international standards: it has a mean value of nearly 14% and varies between zero and 86%. Regulatory quality has a mean value of –0.45, which is well below the world mean of zero and ranges between –2.4 and 0.95. The corresponding standard deviation of 0.68 is much larger than in other regions of the world; for example, the equivalent figure for the European Union is 0.43. The mean value of government share is nearly 10%; 10 out of 378 banks are fully government owned throughout the sample period, 149 are fully private. The mean growth rate is 2.5% with a minimum of –18.0%

[14]Other sources of data, such as the Doing Business surveys, provide more detailed information about contract enforcement, but until very recently the coverage of African countries in these surveys has been limited.

and a maximum of 25%.

Table 3 reveals a correlation of 0.38 between the loans to assets ratio and regulatory quality, an overall pattern consistent with our theoretical results. The correlation between the default rate and the loans to assets ratio is 0.08, which indicates that overall rapid growth in lending is associated with a slightly higher default rate. The growth rate and regulatory quality are highly correlated with a correlation coefficient of 0.38, which is to be expected. There is a smaller correlation of 0.07 between the loans to assets ratio and the growth rate. Finally, government ownership and the default rate are positively correlated with a correlation coefficient of 0.08.

The presence of the lagged dependent variable in the empirical model suggests dynamic panel data estimation (Arellano and Bond 1991, Blundell and Bond 1998). Both the lagged dependent variable and the default rate are likely to be correlated with the error term u_{jt}. Rather than using a classical instrumental variable approach, we apply the two-step GMM method suggested by Blundell and Bond. This involves imposing moment conditions based on the assumption that for each t, Δu_{jt} is uncorrelated with higher-order lags of LA_{jt}, DF_{jt} and $DF_{jt}GV_{jt}$, and similarly that u_{jt} is uncorrelated with lags of ΔLA_{jt}, ΔDF_{jt} and $\Delta[DF_{jt} \cdot GV_{jt}]$.[15] In addition, bank age and RQ_{jt}, which are assumed to be exogenous variables, are used as standard instruments for LA_{jt}, DF_{jt} and $DF_{jt}GV_{jt}$. Given that two-step GMM standard errors are biased, we employ the Windmeijer (2005)

[15]This way of identifying the effect of DF_{jt} on LA_{jt} will be valid so long as shocks to LA_{jt}–for example, shocks to the efficiency with which loans are screened–impact on default rates only with a lag, if at all. Current lending decisions might affect decisions to default in future years, but not in the current year.

correction to obtain robust estimates of the variance-covariance matrix. We use a Sargan Test to check the validity of the over-identifying restrictions in our model, along with tests for first- and second-order autocorrelation in Δu_{jt}.[16] We also carry out a series of robustness checks, including fitting the model using a standard fixed effects estimator (with instruments for the endogenous regressors).

With unbalanced panel data and few annual observations on some banks, we fit several versions of the model with different values of RQ^*. Our main set of results reports the results with $RQ^* = 0$ (the mean value of the Regulatory Quality index for the whole world). Subsequent regressions report results for different values of RQ^*.

Finally, we note that the right hand side of equation (15) does not contain any measure of aggregate economic activity in the country in which the bank operates. With the moral hazard interpretation of the model, there is no particular reason why the loans-to-assets ratio should depend on the aggregate level of economic activity. However, with the adverse selection interpretation, it is possible that aggregate economic activity plays a role. The magnitude of the adverse selection effect might well depend on the number of profitable investment projects available: in periods of high economic growth there will be more opportunities, and fewer borrowers will default because of failed projects. In this case, adding some measure of economic growth to the right hand side of equation (15) constitutes an indirect test of whether the adverse selection or moral hazard interpretation of the model

[16] The Blundell-Bond estimator assumes that u_{jt} is an IID error term, so the first-order test should reject the null of no autocorrelation because the differenced model has MA(1) errors. However, one should not reject zero second-order serial correlation.

is more likely. With adverse selection, higher economic growth should be associated with a significantly higher level of LA_{jt}.

4 Empirical Results

Table 4 presents a set of baseline results for the whole sample, regardless of the level of RQ_{jt}. Two versions of the model are reported, the first of which excludes all interaction terms, imposing the restrictions $\zeta = \eta = 0$. The second version of the model allows for an interaction term between the default rate and government ownership. The diagnostic statistics reported in the table show no sign of model mis-specification: the over-identifying restrictions cannot be rejected; residual autocorrelation tests reject zero first order serial correlation but do not reject zero second order autocorrelation. The lagged dependent variable is significant in the regressions reported in the table, indicating that the choice of a dynamic panel model is appropriate. The coefficient on LA_{jt-1} is close to 0.5, implying that the long run effects of changes in other regressors are roughly twice as large as the short run effects. The quantitative results reported below relate to the effects on impact.

Model 1 gives results consistent with our theoretical model. A percentage point increase in the default rate reduces the loans to assets ratio by a little over 0.2 percentage points; this effect is significant at the 1% level. A unit increase in regulatory quality (an increase equal to one standard deviation in the worldwide sample of governance variables) raises the loans to assets ratio by nearly 5 percentage points; this effect is significant at the 5% level. In Model 2, we see that the government ownership effect is also statistically significant.

For a completely privately owned bank, a percentage point increase in the default rate reduces the loans to assets ratio by over 0.3 percentage points; increasing the governments ownership share by a percentage point reduces this effect by 0.005 percentage points.[17]

Table 5 presents results obtained when we impose a finite value of RQ^* and fit the equation for $RQ_{jt} \leq RQ^*$ to a subset of observations. The table reports results for three values of RQ^*: zero, +0.25 and –0.25. The sample size varies from 314 to 420. The lagged dependent variable and the default rate are statistically significant, and do not vary greatly from one value of RQ^* to another. Regulatory quality enters with a small positive coefficient that is significant for $RQ^* = 0$ and $RQ^* = 0.25$. The interaction term between government ownership and the default rate is also small and positive, suggesting that the negative effect of the default rate is mitigated by government ownership. This term is, however, significant only at the 10% level for $RQ^* = 0$ and $RQ^* = -0.25$; it is insignificant for $RQ^* = 0.25$. The interaction between regulatory quality and the default rate is positive, ranging between 0.39 and 0.48; it is significant at the 5% level for $RQ^* = 0$ and $RQ^* = 0.25$. Regulatory quality mitigates, therefore, the negative effect of the default rate. All three diagnostic statistics are highly satisfactory throughout. Overall, the results in Table 5 provide strong support for our theoretical predictions. In a weak regulatory environment, the default rate has a substantial negative effect on banks' willingness to lend; this effect is mitigated by regulatory quality. Regulatory quality has a positive effect on bank lending, an effect that

[17]This means that for a bank completely owned by the government, the point estimate of the default rate coefficient is positive. However, this point estimate is insignificantly different from zero with a p-value of 0.25.

is greater when the default rate is higher.

Table 6 presents results for $RQ_{jt} > RQ^*$, with $RQ^* = 0$; results for the other values of RQ^* are similar. In Table 6, we do not impose zero coefficients on RQ_{jt} and DF_{jt}, but show that the estimated coefficients are insignificantly different from zero. The point estimate of the default rate coefficient is still negative, but much smaller than in the previous tables, and only one standard error below zero. This is true regardless of whether regulatory quality is included as a regressor. In other words, there is a threshold level of regulatory quality above which small changes in regulatory quality, or in the default rate, have no significant impact on bank behaviour. In good regulatory environments the default rate has no impact on bank lending, as predicted by our theoretical model. Note that the insignificance of the default coefficient in Table 6 is not a consequence of low variability in the default rate in banks operating in a relatively good regulatory environment. The standard deviation of DF_{jt} when $RQ_{jt} > 0$ is 12.7 percentage points, which is only slightly smaller than in the figure for the whole sample (13.9 percentage points).[18] Default rates in Africa do vary widely, even in a relatively good regulatory environment, but in such an environment they appear not to affect bank lending.

Finally, we check whether economic growth has a positive effect on the loans to assets ratio. The economic growth variable is intended to shed some light on whether the root cause of African financial underdevelopment is moral hazard or adverse selection. We expect higher growth rates to lessen adverse selection but to have little or no effect on moral

[18]Moreover, there is no significant difference in *mean* default rates between the cases in which $RQ_{jt} < 0$ and those in which $RQ_{jt} > 0$.

hazard. When an economy is growing fast, the number of good projects will increase while the number of opportunistic borrowers is unlikely to change. Table 7 reports an extension of the first model in Table 4, in which the rate of growth of GDP per capita in the country in which the bank operates (GY) is added as an additional regressor. We provide four different sets of estimates, which vary depending on the treatment of GY. Specifically, we use contemporaneous or lagged values of GY and we treat both of them as exogenous in the first two regressions and as endogenous in the second two. In the latter case, as we use system GMM, the instruments for GY are its own lagged values in the differenced equation and lagged values of its first difference in the levels equation. The results on the significance of GY are unfortunately not very clear, varying not so much by whether it is treated as an endogenous or exogenous regressor but by whether we use contemporaneous or lagged values of GY. When we use contemporaneous values, the growth rate is not significant. When we use lagged values, the GDP growth rate is significant at the 5% level if it is treated as an exogenous regressor. Its significance, however, diminishes to the 10% level when it is treated as an endogenous regressor. It is perhaps more reasonable to attach slightly more weight on the results in which the GDP growth rate is treated as an endogenous variable. It is also perhaps more plausible to expect bank lending to respond to the exogenous component of economic growth reasonably quickly. When a bank is considering which projects to finance, current economic conditions and future prospects are likely more important than last years economic conditions. In that sense, to the extent that the growth rate is a good proxy for cyclical variations in investment opportunities, the evidence indicates, albeit tentatively, that the more likely cause of African financial underdevelopment is strategic loan defaults rather than the lack of good projects.

Robustness Checks

As we have shown in Table 5, the main results of the paper remain valid when using alternative threshold values for RQ^*. Moreover, the main results remain valid if we remove the time fixed effects.[19] In Table 8 we report additional robustness checks involving the use of a simpler estimator, namely fixed effects IV. Although this estimator is biased for small T, we report it for comparison purposes. We report results for all countries and separately for those with above or below RQ^*, for RQ^* set at the world average level. The instruments for the endogenous variables include regulatory quality and lagged values of the endogenous variables (the lagged dependent variable and the default rate). Because fewer instruments, lags and first differences of the variables are used, the sample size is somewhat larger compared to system GMM. In the all-countries results reported in column 1 of Table 8, the default rate is negative and highly significant while regulatory quality is positive but not significant. In the sample that includes the countries with below world average regulatory quality, the default rate remains negative and highly significant with a slightly higher coefficient. In the sample of countries that have above world average regulatory quality, the default rate remains negative but has a much smaller coefficient in absolute terms which is insignificant. Taken together these results provide confirmation of our main finding we obtained using system GMM—default rates are important only for countries that have poor regulatory quality.

[19]These results are not reported in the interest of brevity but are available from the authors upon request.

Policy Analysis

Table 9 reports partial derivatives of the loans to assets ratio with respect to the default rate and regulatory quality at various key points in the sample. The derivatives have been calculated using the model in the first column of Table 5, which corresponds to countries that have below world average regulatory quality (i.e. $RQ^* = 0$). Because of the presence of the lagged dependent variable, these derivatives represent the short-run marginal effects; the implied long-run effects are more than twice the size of the short-run ones.

Since the derivative with respect to the default rate varies with the extent of government ownership, we report it for fully private and fully government owned banks (the fully private bank is the median observation of government ownership in the sample) and at two intermediate values between these two extremes. Because the same derivative also varies with the degree of regulatory quality we report it at three different levels in the sample (all of which are of course below RQ^*): the sample mean of RQ^*, the median which at –0.32 is slightly higher than the mean and the 25^{th} percentile, which is –0.93.

For a fully private bank this derivative is –1.34 and is significant at the 2% level; it declines from –1.29 at the median RQ to –1.53 at the 25^{th} percentile. At the other extreme, for a fully government owned bank this marginal effect has a lower value in absolute terms of –0.92 at mean RQ. It is no longer significant at the conventional 5% level, although it is significant at the 10% level. At the mean value of government ownership, the derivative takes only slightly lower values than the corresponding ones for a private bank and has the same significance level. At 50% government ownership, the derivative increases to –1.13

at mean RQ and to –1.32 at the 25^{th} percentile RQ. Thus, it appears that the default rate has a substantial impact on the loans to assets ratio, which is mitigated somewhat by government ownership and regulatory quality. A reduction in the default rate by 1% for a privately owned bank would increase the loans to assets ratio by 1.3 percentage points in the short-run and by nearly 3.0 percentage points in the long-run. These are economically large effects suggesting that if default rates are reduced, bank lending can indeed take off, even without additional savings mobilisation.

The partial derivatives of regulatory quality, which do not vary with government ownership, are reported for various values of the default rate. At the mean default rate (0.14), the derivative has a value of 0.09 and is highly significant. It declines to 0.07 at the median default rate but remains significant. At the 25^{th} and 75^{th} percentiles it stands at 0.05 and 0.11 respectively and remains highly significant in both cases. An increase in the regulatory quality index by 0.1 at the 75^{th} percentile default rate increases the loans to assets ratio by 1.1 per cent. An increase in the regulatory quality index by 0.1 at the 75^{th} percentile default rate increases the loans to assets ratio by 1.1 per cent in the short-run and by 2.5 per cent in the long-run. These numbers are both plausible and economically large.

5 Concluding Remarks

It has been suggested that the major factor explaining why most banks in Africa choose to remain excessively liquid is a high loan default rate. We explore this conjecture in a theoretical model based on moral hazard or adverse selection among borrowers, and find that loan default matters when the quality of regulations guaranteeing contract enforcement falls below a certain level. Estimation of an econometric model based on a dataset of African banks confirms this result: the importance of loan default as a factor inhibiting bank lending depends on regulatory quality, but in a non-linear way. Above a certain threshold level of regulatory quality, neither improvements in the default rate nor further improvements in regulatory quality will increase bank lending.

These theoretical and empirical results are consistent with both a model based on moral hazard (banks find it difficult to screen out opportunistic borrowers who have no intention of repaying the loan) and a model based on adverse selection (banks find it difficult to screen out borrowers with poor investment projects). However, we also find evidence which indicates that banks' behavior is more or less invariant to the overall economic conditions in which they are operating: when economic growth rises, banks do not lend a significantly larger fraction of their assets. If there is any correlation between economic growth and the availability of profitable investment projects, then this makes the adverse selection explanation less likely.

Our findings are consistent with the presence of threshold effects in the finance-growth relationship found by macroeconomic studies such as Rioja and Valev (2004) and Demetriades and Law (2006). They suggest that a high propensity for borrowers to default does not necessarily deter banks from lending: a sufficiently rigorous regulatory environment will promote a relatively high level of lending despite a high rate of default. In this dimension of economic development—as in others—institutional quality is the binding constraint on the performance of the poorest African nations. Once countries have passed a certain threshold level of institutional quality, then a virtuous finance-growth cycle (an important part of which is the market for bank credit) can be established.

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Appendix A

Table 2: *Summary Statistics*

Variable name	**Number of Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum Maximum**
Loans to assets ratio (LA)	1639	0.496	0.203	0.024	0.982
Default rate (DF)	1639	0.136	0.153	0.000	0.860
Government share (GV)	867	0.095	0.231	0.000	1.000
Regulatory quality (RQ)	1639	–0.446	0.682	–2.369	0.954
Growth rate (GY)	1563	0.025	0.041	–0.177	0.254

Table 3: *Correlation Matrix (832 observations)*

	Loans to assets ratio (LA)	Default rate (DF)	Government share (GV)	Regulatory quality (RQ)
Default rate (DF)	0.084			
Government share (GV)	–0.032	0.085		
Regulatory quality (RQ)	0.380	0.035	0.007	
Growth rate (GY)	0.066	–0.020	0.081	0.375

TABLE 4: *Dynamic Panel Estimation of the Loans to Assets Ratio*

All Banks, 1999–2008

	Model 1	**Model 2**
Lagged dependent variable (LA_{-1})	0.498***	0.594***
(*standard error*)	(0.089)	(0.083)
Default rate (DF)	–0.208***	–0.337***
(*standard error*)	(0.062)	(0.131)
Regulatory Quality (RQ)	0.046*	0.062***
(*standard error*)	(0.027)	(0.019)
Government ownership (GV)$\times$ Default rate (DF) $\div$ 10		0.050***
(*standard error*)		(0.020)
Number of observations	847	491
Number of banks	195	110
Sargan test: number of restrictions	32	50
test statistic	39.97	50.38
(*p-value*)	(0.16)	(0.46)
Order 1 correlation test	–4.46	–3.76
(*p value*)	(0.00)	(0.00)
Order 2 correlation test	–1.05	–0.95
(*p value*)	(0.29)	(0.34)

Notes:

1. Estimations are carried out in Stata 11.0 using the xtdpd command. Two step estimates are reported.
2. GMM instruments include lags and first differences of lags of the dependent variable and the default rate(including interaction terms when present). Additional standard instruments for the differenced equation include regulatory quality, bank age and time dummies.
3. All regressions include a full set of time dummies.
4. Figures in parentheses are robust standard errors obtained using the Windmeijer WC-robust estimator.
5. The Null Hypothesis for the Sargan test is that the over-identifying restrictions are valid. The test statistic is distributed as χ^2 with degrees of freedom equal to the number of restrictions.
6. *** indicates a coefficient significantly different from zero at the 1% level; ** corresponds to the 5% level and * the 10% level.

TABLE 5: *Dynamic Panel Estimation of the Loans to Assets Ratio*

Countries with Poor Regulatory Quality ($RQ \leq RQ^*$), 1998–2008

	$\boldsymbol{RQ^* = 0}$	$\boldsymbol{RQ^* = 0.25}$	$\boldsymbol{RQ^* = -0.25}$
Lagged dependent variable (LA_{-1})	0.569***	0.539***	0.552***
(*standard error*)	(0.092)	(0.120)	(0.105)
Default rate (DF)	–1.168***	–1.294**	–1.353***
(*standard error*)	(0.479)	(0.558)	(0.592)
Regulatory Quality (RQ)	0.039**	0.042***	0.020
(*standard error*)	(0.019)	(0.016)	(0.019)
Government ownership (GV)$\times$ Default rate (DF) $\div$ 10	0.042*	0.045	0.043*
(*standard error*)	(0.025)	(0.028)	(0.026)
Regulatory quality (RQ)$\times$ Default rate (DF)	0.388**	0.436**	0.476*
(*standard error*)	(0.196)	(0.212)	(0.261)
Number of observations	373	420	314
Number of banks	90	95	80
Sargan test: number of restrictions	64	65	64
test statistic	61.85	61.69	63.26
(*p-value*)	(0.55)	(0.59)	(0.50)
Order 1 correlation test	–3.13	–3.12	–2.80
(*p value*)	(0.00)	(0.00)	(0.01)
Order 2 correlation test	–1.02	–0.94	–1.06
(*p value*)	(0.31)	(0.35)	(0.29)

Notes: See Table 4.

Table 6: *Dynamic Panel Estimation of the Loans to Assets Ratio*

Countries with Good Regulatory Quality (RQ > RQ), 1998–2008*

	Model 1	Model 2
Lagged dependent variable (LA_{-1})	0.746***	0.633***
(*standard error*)	(0.126)	(0.124)
Default rate (DF)	–0.137	–0.119
(*standard error*)	(0.131)	(0.151)
Regulatory Quality (RQ)	–0.045	
(*standard error*)	(0.051)	
Number of observations	197	348
Number of banks	56	146
Sargan test: number of restrictions	31	43
test statistic	34.32	50.63
(*p-value*)	(0.31)	(0.20)
Order 1 correlation test	2.28	–2.82
(*p value*)	(0.02)	(0.00)
Order 2 correlation test	0.96	1.05
(*p value*)	(0.33)	(0.29)

Notes: See Table 4.

TABLE 7: *Dynamic Panel Estimation of the Loans to Assets Ratio Including GDP Growth, All Banks, 1999–2008*

	Treatment of Growth Rate			
	Exogenous	**Exogenous**	**Endogenous**	**Endogenous**
Lagged dependent variable (LA_{-1})	0.540***	0.559***	0.497***	0.591***
(*standard error*)	(0.082)	(0.077)	(0.084)	(0.071)
Default rate (DF)	–0.197***	–0.213***	–0.178***	–0.220***
(*standard error*)	(0.062)	(0.060)	(0.062)	(0.057)
Regulatory Quality (RQ)	0.067***	0.044*	0.052***	0.040**
(*standard error*)	(0.023)	(0.024)	(0.020)	(0.020)
GDP growth rate (GY)	–0.175	–	0.020	–
(*standard error*)	(0.169)		(0.144)	
Lagged GDP growth rate	–	0.418**	–	0.551*
(*standard error*)		(0.186)		(0.294)
Number of observations	831	840	831	840
Number of banks	194	195	194	195
Sargan test: number of restrictions	32	32	50	50
test statistic	41.81	37.43	67.30	57.35
(*p-value*)	(0.11)	(0.23)	(0.05)	(0.22)
Order 1 correlation test	–4.91	–4.80	–4.46	–4.75
(*p value*)	(0.00)	(0.00)	(0.00)	(0.00)
Order 2 correlation test	0.66	–0.93	0.513	–0.91
(*p value*)	(0.51)	(0.35)	(0.61)	(0.36)

Notes: See Table 4.

Table 8: *Dynamic Panel Estimation of the Loans to Assets Ratio*

Robustness Checks: Fixed Effects IV Estimations

	All countries	$\boldsymbol{RQ > 0}$	$\boldsymbol{RQ < 0}$
Lagged dependent variable (LA_{-1})	0.179***	0.253**	0.156*
	(0.075)	(0.128)	(0.091)
Default rate (DF)	–0.251***	–0.120	–0.306***
	(0.097)	(0.148)	(0.118)
Regulatory Quality (RQ)	0.013	0.097**	–0.003
	(0.018)	(0.045)	(0.022)
Number of observations	1193	297	896
Number of banks	320	86	260
R^2 (overall)	0.47	0.49	0.23
F-test	1.33	1.89	1.09
(*p value*)	(0.00)	(0.00)	(0.21)

Notes:

1. All regressions report results without time dummies, which are statistically insignificant.
2. Default rate and lagged loans to assets ratio are treated as endogenous variables. They are instrumented by their lagged values.
3. Figures in parentheses under estimated coefficients are standard errors.
4. The F-test tests the significance of the bank fixed effects.
5. *** indicates a coefficient significantly different from zero at the 1% level; ** corresponds to the 5% level and * the 10% level.

Table 9: *Policy Analysis*

Partial Derivates of the Loans to Assets Ratio

	Per cent of government ownership			
	0%	**9.6% (mean)**	**50%**	**100%**
A. Partial derivative with respect to default rate at				
mean RQ (–0.446)	–1.341	–1.301	–1.131	–0.920
	(0.02)	(0.02)	(0.04)	(0.09)
median RQ (–0.318)	–1.291	–1.251	–1.081	–0.871
	(0.02)	(0.02)	(0.03)	(0.09)
25^{th} percentile of RQ (–0.926)	–1.530	–1.487	–1.317	–1.107
	(0.02)	(0.02)	(0.04)	(0.08)

	Default rate			
B. Partial derivative with respect to regulatory quality at	**25^{th} percentile (0.031)**	**median (0.079)**	**mean (0.136)**	**75^{th} percentile (0.189)**
	0.051	0.070	0.092	0.112
	(0.00)	(0.00)	(0.00)	(0.00)

Notes:

1. The partial derivatives are estimated using the results reported in Table 5 with $RQ^* = 0$.
2. Figures in parentheses are p-values for the test of statistical significance of the marginal effects.

Appendix B: Data

The main source of the banking data is Bank Scope (Bureau van Dijk). The source of the governance indicators is the World Bank.

Variable definitions (Source)

Loans-assets ratio: The ratio of loans to total assets (Bank Scope).

Default rate: the ratio of impaired loans to total loans (Bank Scope).

Government share: the percentage of shares owned by Government (Bank Scope).

Regulatory Quality: An index constructed by the World Bank capturing 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. 2009).

Table 10: *Number of Banks in Each Country*

Country	Number	Country	Number	Country	Number
Algeria	2	Guinea	1	Niger	3
Angola	5	Guinea Biss.	1	Nigeria	60
Benin	7	Kenya	54	Rwanda	4
Botswana	11	Lesotho	3	South Africa	43
Cameroon	4	Liberia	1	Senegal	3
Cape Verde	4	Libya	2	Seychelles	1
C.A.R.	1	Madagascar	4	Sierra	1
Chad	3	Malawi	6	Sudan	3
Cote d'Ivoire	7	Mali	4	Swaziland	5
Egypt	5	Mauritiania	4	Togo	7
Eritrea	2	Mauritius	12	Tunisia	23
Ethiopia	8	Morocco	6	Zambia	11
Gabon	1	Mozambique	10	Zimbabawe	28
Ghana	11	Namibia	7		