Competition, Information Sharing and Bank Efficiency:
Some International Evidence

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Abstract: This study uses the non-parametric double bootstrapping DEA method proposed by Simar and Wilson (2007) to examine the effects of banking competition and information sharing via credit agencies on bank efficiency. Using accounting data of close to more than 1200 banks across 69 countries from Bankscope, the unique World Bank banking regulation dataset compiled by Barth, Caprio and Levine (2006), and information sharing database assembled by Djankov, McLiesh, and Shleifer (2007), we find strong evidence that both banking competition and information sharing increase bank efficiency and that information sharing further enhances the positive impact of bank competition on bank efficiency. We also find that supervisory independence and bank accounting disclosure have positive effect on bank efficiency and state ownership of banking sector is associated with lower efficiency. Our empirical results are robust to controlling for different macroeconomic and institutional variables and endogeneity tests as well.

JEL Classification: G21, L1, O16

Keywords: Competition, Information Sharing, Bank regulation, Bank Efficiency

1. Introduction

Banking efficiency is essential for well-functioning and development of the economy. Researches suggest that banks exert a first-order impact on economic development (e.g., Levine 1997). When banks operate efficiently by directing the society's savings toward those enterprises with highest expected social returns and monitoring them carefully after lending, the society's scarce resources are allocated more efficiently. This will in turn promote economic growth. By contrast, banks that simply operate with waste and inefficiency will slow economic growth and reduce society's economic welfare.

In this paper, we use a large sample of cross-country banking firm data to measure bank operation efficiency and study the effect of bank competition and information sharing on the efficiency measure. We argue that both bank competition and credit information sharing mechanisms help enhance bank operation efficiency. In addition, we argue that information sharing mechanisms such as credit registries help to level the information field and induce more competition in banking. This in turn helps increase bank efficiency.

We measure bank operation efficiency with a non-parametric method—Data Envelope Analysis (DEA). The constructed relative efficiency frontiers are non-parametric in the sense that they are constructed through the envelopment of the banks, with the "best practice" banks forming the non-parametric frontier. The advantage of non-parametric techniques such as DEA, relative to parametric techniques such as stochastic frontier analysis or production function approach, is that the latter has to assume a particular functional form to estimate with data on sales revenue, input costs, and other bank characteristics. Hence, any resultant efficiency scores will be partially dependent on how accurately the chosen functional form represents the true production relationship. As DEA is non-parametric and envelops the input/output data of banks under consideration, the derived efficiency results do not suffer from this problem of functional form dependency (e.g., Banker and Maindiratta, 1988; Drake et al 2006)[1]. Furthermore, recent development of the two-stage bootstrapping DEA (e.g., Simar and Wilson 2007) allows random errors in the model and it is able to correct for the

[1] As will be discussed in more detail later, some researchers use interest margin to measure bank intermediation efficiency. However, they also acknowledge that the interest margin measure might reflect many other factors than bank efficiency (Demirguc-Kunt et al 2004; Barth et al, 2006).

estimation bias that the traditional DEA could not deal with[2].

There is an extensive literature on efficiency of financial institutions (e.g., see an excellent survey by Berger and Humphrey 1997 on more than 130 empirical studies in the field). According to Berger and Humphrey (1997), the bank efficiency literature performs two tasks. The first task is to evaluate performance of banks and separate better performed banks from worse ones. This is done by applying non-parametric or parametric frontier analysis to firms within the banking industry or to branches within a bank. The second task is to use the efficiency measures to inform government policies, to improve managerial performance by identifying ‘best practices’ and ‘worst practices’, and to address other research issues. The efficiency estimates from nonparametric (e.g., DEA) studies are similar to those from parametric frontier models, but non-parametric methods generally yield slightly lower mean efficiency estimates and seem to have greater dispersion than the results of the parametric models. In performing the second task, the government policy-efficiency literature finds that deregulation of financial institutions can either improve or worsen efficiency, depending upon industry conditions prior to deregulation. Firm efficiency appears to be greater for some forms of corporate organization or control than others, though most of these effects are economically insignificant. However, the empirical studies in the bank efficiency literature mostly focus on the U.S. market and some recent ones only examine a limited number of OECD or EU countries, or transition countries (e.g., Berg et al 1993; Fecher and Pestieau, 1993; Bergendahl 1995; Allen and Rai, 1996; Pastor et al., 1997; Altunbas and Chakravarty 1998; Bonin et al 2005). In our paper, we use bank data from a large number of diverse countries, including developed, developing, and transition countries, to study the bank efficiency issue.

There also exists a large body of empirical studies on the relationship between bank competition and bank efficiency (e.g., see an excellent survey by Berger et al 2004). Many studies find a positive statistical relationship between bank concentration and profitability.

[2] The traditional DEA approach implicitly assumes that all departures from the production frontier are due to technical inefficiency without regards to potential impacts of measurement errors and other random noises. Such a restrictive assumption is relaxed in the stochastic frontier analysis (SFA). This was viewed as a comparative advantage of SFA relative to DEA.

This positive relationship may be due to the market power of the concentrated banks or alternatively, the higher concentration may be the result of competition of higher efficiency of some banks (Demsetz 1973). The evidence comparing market power and efficiency effect is limited, but it suggests that cost efficiency is somewhat more important than market power in explaining profitability (Berger and Humphrey 1997). Unfortunately, most of the earlier researches on this topic have been on the U.S. banking industry, where the structure of the industry is quite different from the rest of the world[3].

More recently, there are some studies using international data (e.g., see a survey by Berger et al 2004)[4]. The new research recognized problems with traditional concentration measures such as Herfindahl Index and n-firm concentrations and specified alternative measures of competitiveness. These new indicators include regulatory restrictions on bank competition, bank entry restrictions, openness of trade and other legal impediments to bank competition. For examples, Demiguc-Kunt, Laeven, and Levine (2004) use data on 1,400 banks across 72 countries and find that tighter regulations on bank entry, restrictions on bank activities, and regulations that inhibit the freedom of bankers to conduct their business all boost net interest margins (lower intermediation efficiency according to their interpretation). However, they also find that the weak positive relationship between bank margins and concentration breaks down when controlling for institutional development. They suggest exercising caution when use bank concentration to proxy the competition environment of the banking market. Barth et al (2004, 2006) examine the effect of an array of regulations on bank performance such as bank development, efficiency, risk, and integrity in lending. They also use the net interest margin and overhead cost as measures of bank intermediation efficiency but they admit that these measures are subject to some problems. These measures could capture other factors that are not related to bank efficiency. For example, banks are increasingly engaging in other fee-based activities and these activities will not be reflected in

[3] The US banking market is much more un-concentrated than most of the other countries. For example, it takes more than 2,000 banks to account for 90% of deposits in the U.S. while most other developed countries only need 10 banks to do that (e.g., Berger and Humphrey 1997).

[4] The earlier studies (before 1990s) examine the effects of bank concentration and competition with the traditional structure-conduct-performance (SCP) hypothesis. The SCP hypothesis argues that bank concentration and other impediments to competition create an environment that affects bank performance unfavorably to society as a whole (e.g., Berger et al 2004).

the net interest margin and overhead cost. Higher interest margin may also simply due to banks' lending to high risk borrowers. In our paper, we try to overcome this deficiency by adopting the non-parametric DEA efficiency measure[5]. We also follow the new research literature and use bank entry barriers as measure of bank competition, in addition to traditional measures of concentration of banking assets or deposits.

There is also a growing body of both theoretical and empirical studies on the role of information sharing in bank and credit market performance. One of the theoretical studies is by Pagano and Jappelli (1993), which shows that information sharing mechanisms reduce adverse selection by improving the pool of borrowers and therefore improve bank efficiency in the allocation of credit. It can also be valuable in addressing moral hazard problems through its incentive effects on curtailing imprudent borrower behavior (Padilla and Pagano, 1997). In addition, Padilla and Pagano (1997) shows that information sharing helps reduce information rent that banks can otherwise extract from their clients, reduce or even eliminate the information advantage of larger size banks and therefore enhances credit market competition and efficiency. Some empirical studies confirm that credit bureau help reduce the selection costs of lenders by allowing them to more accurately predict individual loan defaults (Barron and Stein, 2003; Kallberg and Udell, 2003). There are also studies documenting the evidence that information sharing affect bank lending, default, or firms access to credit (e.g., Jappelli and Pagano 2002; Brown, Jappelli, and Pagano 2007). For examples, Jappelli and Pagano (2002) find that bank lending is higher and credit risk is lower in countries where lenders share information, regardless of the private or public nature of information sharing mechanism. Brown et al (2007) show that information sharing is associated with improved availability and lower cost of credit to firms, and that this correlation is stronger for opaque firms than transparent firms. Djankov et al (2007) provide evidence that shows that private credit rises after improvements in creditor rights and in information sharing. However, the above studies do not address the effect of information sharing on bank operation efficiency directly. Our paper provides first empirical evidence on this important issue.

[5] As will discussed in more detail in later, the DEA measure is superior to traditional techniques based financial ratios because it summarizes performance in a single statistic that controls for differences among banks.

We measure bank competition in two different ways: one with concentration of deposits (or assets) and another with measures of entry barriers in banking. As argued in the traditional literature on bank competition, higher concentration of deposits or assets is a reflection of some monopoly power in the banking industry and hence less competitive banking environment. However, as pointed out by Berger et al (2004), the concentration measure may endogenously reflects the market share gains of efficiency firms rather than an exogenous measure of competition. Therefore, we supplement the concentration measure with measures of bank entry barriers which reflect the contestability of the banking industry in each country. Both the concentration and the contestability measures come from a recently available and expanded dataset collected by Barth et al (2006).

Bank information sharing data come from Doing Business Survey by The World Bank and is used in a recent paper by Djankov et al (2007). The World Bank Doing Business Survey collects data on the existence of public (i.e., government-owned) and private credit registries in a number of countries during the period 1978-2003. These registries collect information on credit histories and current indebtedness of various borrowers and share it with lenders. The Public Credit Registries (PCRs) are generally managed by central banks, and access is granted only to authorized central bank staff (mainly for surveillance reasons and under tight confidentiality rules and to the reporting financial institutions). A private credit registry is owned and managed by private sector and it can issue several kinds of credit reports, including past defaults or arrears - “negative” data - to pattern of repayments, employment and family history - “positive” data. Private credit bureaus generally are less complete in their coverage but offer details on individual loans and merge credit information with other data (see Jappelli and Pagano 2005).

Our main results can be summarized as following. First, banking competition as measured by lower asset (deposit) concentration and/or entry barriers enhances bank efficiency. This result supports the positive role of competition in improving bank performance. Second, information sharing mechanisms measured by the existence and depth of credit registries also increase bank efficiency, supporting the positive role of information sharing in banking operation. Third, information sharing further enhances (attenuates) the effect of bank competition (concentration or entry barriers) on bank efficiency.

Beyond these major findings, we also obtain some other results. We find that higher bank accounting quality and independence of supervisory authority are associated with greater bank efficiency. A banking system dominated by government ownership is associated with lower banking firm efficiency. Large and highly leveraged banks tend to have higher efficiency. Finally, a country with large GDP and GDP per capita seem to facilitate more efficient banks while inflation is negatively associated with efficiency.

We perform a number of robustness tests on our results. Specifically, we expand our control variables by including major macro-economic and institutional measures. We examine the potential endogeneity issue in our analysis by performing IV regressions. We also try to provide some further corroborating evidence to support the hypothesis that bank competition and information sharing have causal impacts on levels of bank operation efficiency by splitting samples according to country, industry, and firm characteristics and study their interaction effects.

The rest of paper is organized as follows. Section 2 summarizes the theory concerning the effects of bank competition and information sharing on bank performance and credit market. It also develops key hypotheses on the effect of competition and information sharing on bank efficiency. Section 3 discusses the DEA methodology and its implementation procedures. Section 4 presents the data and defines the variables in the following analysis. Section 5 presents and discusses the empirical findings. Section 6 provides robustness analysis of our major findings and some extensions. Section 7 concludes the paper with discussions on our contributions to the literature and some policy implications.

2. Theory and Hypothesis

Economic theory provides conflicting predictions on the effects of bank concentration on bank efficiency. For example, one view is that a concentrated banking market allows a few powerful banks dominate and stymie competition with deleterious implications for efficiency (e.g., Berger et al 2004; Demirguc-Kunt, Laeven and Levine 2004). Monopoly power induces inefficiency and waste while the pressure of a competitive market creates incentives for managers to perform and provides information to design appropriate incentive schemes (e.g., Hart 1983; Schaferstein 1988; Allen and Gale 2000; Vives 2000). However, an alternative view is that more efficient banks have lower costs and garner greater market share (Demsetz 1973; Peltzman 1977) and hence concentration may be associated with more efficiency.

By contrast, the contestable market theory suggests that concentration is not directly related to competition and efficiency; what matters to bank competition are other regulatory and legal impediments to bank entry (Berger et al 2004). A contestable market facilitates more competition and should help enhance bank efficiency. Therefore, in our empirical analysis, we distinguish the effects of concentration and contestability on bank efficiency. Our arguments lead to our first main hypotheses as follows.

Hypothesis 1A. Bank concentration as measured by concentration of bank assets and deposits reduces bank efficiency

Hypothesis 1B. Bank competition as measured by less entry barriers enhances bank efficiency

Bank information sharing in the form of credit registries should help enhance bank efficiency. As is well known, banks are subject to the problem of asymmetric information in which borrowers have more information about their projects than lenders. Asymmetric information in banking could lead to adverse selection and moral hazard problem and prevent efficient allocation of capital (e.g., Jaffee and Russell 1976; Stiglitz and Weiss 1981). Information sharing among lenders helps reduce both the adverse selection and moral hazard problems. First, credit registries improve banks' knowledge of applicants' characteristics and permit more accurate predictions of repayment probability. This allows lenders to target and price their loans better, easing adverse selection problems. Pagano and Jappelli (1993) show that information sharing help reduce adverse selection by improving the pool of borrowers. In their model, each bank has private information about local credit applicants but has no information about non-local credit applicants. Therefore, the bank faces adverse selection from the second group of potential borrowers. By sharing information, banks can also assess the quality of non-local credit seekers and lend them as efficiently as they do with local borrowers. The information also allows banks to promote financial instruments and set and manage credit limits better. In short, information sharing play a key role in improving the efficiency of financial institutions by reducing loan processing costs as well as the time required to process loan applications (Miller 2003)[6].

Second, credit registries also work as a borrower discipline device: every borrower knows that if he defaults, his reputation with all other potential lenders is ruined, cutting him off from credit or making it more expensive to get further credit. These mechanisms tighten borrowers' incentives to repay, reducing moral hazard. Alternatively, Padilla and Pagano (1997) built a two-period model where banks have private information about their borrowers. The information advantage confers to banks some market power over their borrowers, and generates a hold-up problem: knowing that banks will charge predatory rates in the future, borrowers exert low effort to perform. If banks commit themselves to share information about borrowers' type, however, banks restrain their own future ability to extract information rents, leaving a large portion of the surplus to entrepreneurs. As a result, these entrepreneurs will exert greater effort in their projects, reducing the moral hazard problem in bank loans. Exchanging information about borrowers' debt exposure also removes the particular form of moral hazard deriving from borrowers' ability to borrow from multiple lenders. Bennardo, Pagano, and Piccolo (2007) show that the danger of over-lending that stems from a customer borrow from several banks may result in inefficiency in allocating scarce credit. As information sharing makes lending safer, it should help enhance efficiency in credit allocation process. Therefore, we have the following hypothesis.

Hypothesis 2. Bank information sharing mechanisms help enhance bank efficiency

Finally, information sharing mechanisms also enhance banking competition by reducing

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[6] According to some case studies reported by Miller (2003), the cost and time in allocating credits reduce significantly after the introduction of information sharing and credit scoring mechanisms. For instance, the loan processing time decreased from 9 days to 3 days in a bank in Canada in 18 months since the information sharing and credit scoring was implemented. The average processing time of a bank in Netherlands decreased from 8-10 hours to 15 minutes for existing clients and 45 minutes for new clients. In a bank in the U.S., the average cost of process a small business loan decreased from $250 to $100 after implementing the information sharing and credit scoring system.

information rent that banks extract from their clients and leveling the informational playing field within the credit market. Banking competition also strengthens the positive effect of information sharing: when credit markets are contestable, information sharing reduces informational rents and increases banking competition. The increased competition in credit market will further increase bank efficiency. These arguments lead to our third hypothesis.

Hypothesis 3. Bank information sharing enhance (reduce) the effect of bank competition (concentration and/or entry barriers) on bank efficiency

In addition to the above three main hypotheses, we also examine other determinants of bank efficiency. More specifically, in our regression framework, in addition to putting the main explanatory variables such as measures of bank competition and information sharing, we control for variables such as bank regulations, ownership of banking industry, bank size and leverage. We also control some macroeconomic variables such as country's inflation rate, GDP and GDP per capita.

3. Methodology and implementation procedures

In this paper, we apply a recently developed two-stage, double bootstrapping data envelopment analysis (DEA) approach (Simar and Wilson, 2007) to examine the relationship between bank efficiency, information sharing, and competition. There are four major advantages of applying the DEA approach in our context.

First, the DEA is a nonparametric approach and does not impose assumption of any specific production functional form. It is an extension of earlier nonparametric analysis of productivity by Afriat (1972) and Varian (1984) to allow individual banks to deviate from their profit maximization frontier and therefore to exhibit some degree of inefficiency (Banker and Maindiratta, 1988). In other words, the DEA approach measures a bank's performance relative to 'best practice' frontiers derived from its peer group (Farrell, 1957). Such a measure is superior to traditional techniques such as financial ratio analysis because the DEA summarizes performance in a single statistic that controls for differences among banks using a sophisticated multidimensional framework. Frontier efficiency analysis can be used in a number of ways to assist a bank to evaluate whether it is performing better or worse than its peer group in terms of technology, scale, cost minimization and revenue maximization and thus to direct management efforts to the areas that most need improvement. The DEA approach as an efficient frontier method has been employed increasingly in the finance literature (e.g., Berger et al 1997).

Second, Simar and Wilson (2007) show that their two-stage bootstrapping DEA overcomes the drawback of the traditional DEA that assumes no random error in the model (Berger and Humphrey, 1997). It is also a valid procedure to correct for other estimation bias due to heteroskedascity and serial correlation documented in the previous literature. Third, the DEA focuses on the individual observations rather than on population average, compared with the regression analysis. According to Banker and Natarajan (2007), the simulation results indicate DEA-based procedures perform better than parametric methods in the estimation of individual decision making unit (individual bank in our case) productivity. Fourth, it compares bank performance to the revealed best-practice frontier, rather than on the central-tendency properties of the frontier. The DEA methodology has been widely used in economics and finance literature, as reviewed by, for example, Cooper et al. (2004). Therefore, we employ the two-stage DEA approach of Simar and Wilson (2007) in this study.

3.1. The two-stage bootstrapping DEA methodology

The two-stage estimation in the double bootstrapping data envelopment analysis (DEA) is developed by Simar and Wilson (2007). In the first-stage estimation, the DEA methodology computes an operational efficiency score for each bank in the sample. The second-stage estimates the determinants equation of the efficiency score.

The operational efficiency score for a bank is estimated as the fraction of actual inputs that is required for the bank to be located on the efficient frontier to produce the same level of output. Suppose the sample size is n and there are m inputs and s outputs for each bank. Denote $x_k = (x_{1k}, x_{2k}, \ldots, x_{mk})$ as a mx1 vector of inputs for bank k, $X=(x_1, x_2, \ldots, x_n)$ as a $m \times n$ matrix of inputs, $y_k = (y_{1k}, y_{2k}, \ldots, y_{sk})$ as a $s\times1$ vector of outputs for bank k, and $Y=(y_1,$

$y_2, \ldots, y_n$) as a $s \times n$ matrix of outputs, respectively. The variable returns to scale DEA model can be expressed with the following n linear programming problems for each bank k (k=1, 2,…n):

$$\text{Max}(\varphi_k \geq 1 \mid x_k, y_k, X, Y) = \text{Max}(\varphi_k \geq 1 \mid \varphi_k y_k \leq Y\lambda_k, X\lambda_k \leq x_k, \lambda_k \geq 0, I_1'\lambda_k = 1) \quad (1)$$

where I_1 denotes an $n\times1$ vector of ones, φ_k denotes a scalar parameter, and $\lambda_k = (\lambda_{1k}, \lambda_{2k}, \ldots, \lambda_{nk})'$ denotes a $n\times1$ non-negative vector of parameters.

The output-oriented efficiency score $e_k=1/\varphi_k$ ($0\leq e_k\leq1$) for bank k. Under the DEA method, a bank with an efficiency score of unity (100%) is located on the efficient frontier in the sense that its outputs cannot be further expanded without increasing its inputs. A bank with an efficiency score below 100% is relatively inefficient. In the first stage estimation, we have three inputs and three outputs to estimate efficiency scores for each bank in the sample based on model (1) (see Section 4.2 below for details).

In the second stage, we estimate the following equation to identify the determinants of the banking efficiency score e_k :

$$e_k = \sum_j \beta_j X_{k,j} + u_k \quad (2)$$

where e_k is the efficiency score for bank k. $X_{k,j}$'s are explanatory variables including a constant term, which represent information sharing and competition proxies, as well as other control variables such as bank regulation, bank characteristics, and macroeconomic environment discussed in Section 4. u_k is an error term with a standard error of σ_u. Since efficiency scores e_k are truncated below from zero and above from unity, u_k is an error term with double-truncation.

A common practice in the DEA-literature is to estimate equation (2) with a Tobit model. However, Simar and Wilson (2007) demonstrate that the Tobit model is invalid due to complicated, unknown serial correlation among the efficiency estimates. They propose an alternative two-stage, bootstrap truncated regression that permits valid inference. It is a bias-corrected and heteroskedasticity-consistent approach. In this paper, we apply their two-stage estimation procedure, in particular their 'Algorithm 2' (Simar and Wilson, 2007, p.42-43), to investigate the main issues discussed in the previous section. This procedure can be summarized as follows.

3.2. Implementation procedures

Stage I Estimation

Step 1. Estimate efficiency scores $\hat{e}_k$ based on (1) for all banks in the sample, *k*=1, 2, … , *n*.

Step 2. Estimate the parameter vector $\hat{\beta}$ and the standard error $\hat{\sigma}_u$ by the truncated regression model (2).

Step 3. Repeat the following four sub-steps B_1 times to obtain the bootstrapped $\{\hat{e}^*_{kb}\}$ (*k*=1, 2, … , *n*, and *b*=1, 2,…, B_1):

Step 3.1. Randomly draw u^*_{kb} (*k*=1, 2, … , *n*) from N(0, $\hat{\sigma}^2_u$) distribution with left-truncation $\left(-\sum_j \beta_j X_{k,j}\right)$ and right-truncation $\left(1-\sum_j \beta_j X_{k,j}\right)$.

Step 3.2. Compute $e^*_{kb} = \sum_j \beta_j X_{k,j} + u^*_{kb}$ for *k*=1, 2, … , *n*.

Step 3.3. Let $y^*_{kb} = y_k e^*_{kb} / \hat{e}_k$ for *k*=1, 2, … , *n*.

Step 3.4. Replace *Y* by Y^*_b=($y^*_{1b}, y^*_{2b}, \cdots, y^*_{nb}$) in (1) and re-estimate $\hat{\varphi}^*_{kb}$=Max($\varphi_k \geq 1 \mid x_k$, y_k, *X*, Y^*_b), and let $\hat{e}^*_{kb}$=1/$\hat{\varphi}^*_{kb}$ for *k*=1,2, … , *n*.

Step 4. Compute bias-corrected estimator $\hat{\hat{e}}_k = \hat{e}_k - BIAS(\hat{e}_k)$, where

$BIAS(\hat{e}_k) = \frac{1}{B_1}\sum_b \hat{e}^*_{kb} - \hat{e}_k$ (Simar and Wilson, 2000).

Stage II Estimation

Step 5. Re-estimate the parameter vector $\hat{\hat{\beta}}$ and the standard error $\hat{\hat{\sigma}}_u$ by the truncated regression of $\hat{\hat{e}}_k$ on $X_{k,j}$ via model (2).

Step 6. Repeat the following three sub-steps B_2 times to obtain the bootstrapped $\{\hat{\beta}^*_b, \hat{\sigma}^*_b\}$,

b=1, 2, … , B_2 :

Step 6.1. Randomly draw u_{kb}^{**} (k=1, 2, … , n) from N(0, $\hat{\hat{\sigma}}_u^2$) distribution with left-truncation $\left(-\sum_j \hat{\hat{\beta}}_j X_{k,j}\right)$ and right-truncation $\left(1-\sum_j \hat{\hat{\beta}}_j X_{k,j}\right)$.

Step 6.2. Compute $e_{kb}^{**} = \sum_j \hat{\hat{\beta}}_j X_{k,j} + u_{kb}^{**}$ for k=1, 2, … , n.

Step 6.3. Estimate the bootstrapped parameter vector $\hat{\hat{\beta}}_b^{**}$ and the standard error $\hat{\hat{\sigma}}_{ub}^{**}$ by the truncated regression of e_{kb}^{**} on $X_{k,j}$ via model (2).

Step 7. Use the bootstrapped parameter vector $\hat{\hat{\beta}}_b^{**}$ and the standard error $\hat{\hat{\sigma}}_{ub}^{**}$ to estimate the significance levels (p-values) of all the parameters.

4. Data and Variables

4.1 The Sample

The dataset used in this study is compiled from three main sources: (1) the BankScope database provided by Bureau van Dijk and Fitch Ratings, (2) Barth, Caprio, and Levine (BCL henceforth) (2006) dataset on bank supervision and regulation in 152 countries, (3) and the Djankov, McLiesh, and Schleifer (DMS henceforth) (2007) and World Bank "Doing Business" dataset on information sharing in 178 countries. Bank-level information from 69 countries on about 1200 banks is from the BankScope database. The BankScope database has comprehensive coverage in most countries, accounting for over 90% of all banking assets. Each bank report contains detailed balance sheet and income statement totaling up to 200 data items and 36 pre-calculated financial ratios. In this study, we mainly use the most recent data reported in year 2006[7]. The banking competition and ownership data come from BCL (2006), which were compiled based on a World Bank survey on bank regulation and supervision in 152 countries in year 2003. The information-sharing variables come from DMS (2007) and World Bank "Doing Business" Dataset (2005), which contain data on

[7] We have also estimated DEA measures with three-year (2004-2006) data and report the three-year average results in Table 8. The findings with three year data are robust.

information sharing credit institutions in 178 countries. Because of the incomplete overlap among the three datasets and missing firm-level and banking-sector variables, the final sample used in our study includes 1181 enterprises in 69 countries all over the world[8].

In addition to the three datasets mentioned above, we rely on two other data sources, the World Development Indicator (WDI, 2004) and the World Governance Indicator compiled by Kaufmann et al. (2006) to control for macro- institutional factors that might affect the overall level of bank corruption in a country. Tables 1 and 2 identify the data sources and provide brief descriptions and summary statistics of the key variables.

[Tables 1 and 2 here]

4.2. Bank Efficiency

We use the standard *financial intermediation approach* to evaluate the relative efficiency of banks. The *financial intermediation approach* was originally developed by Sealey and Lineley (1977) and posits that total loans and securities are outputs, whereas deposits along with labor and physical capital are inputs. The approach was thereafter widely adopted and used. Following the recent applications (e.g. Casu, Girardone and Molyneux, 2004; Drake, Hall and Simper, 2006), we posit an intermediation model that has three inputs and three outputs. The inputs (Xi) are: X1 (total deposits+ total money market funds + total other funding); X2 (personnel expenses-labor input); and X3 (total fixed assets-physical input). With respect to the three outputs (Yi), we have: Y1 (total customer loans + total other lending); Y2 (total other earning assets— other interest generating or fee yielding assets such as bonds and investment securities); and Y3 (other, non-interest, income). The efficiency scores are evaluated using the bootstrapping DEA method described previously and summarized across countries in table 3. The estimation is based on Simar and Zelenyuk (2007) group-wise heterogeneous sub-sampling procedure, with 2,000 bootstrap replications both for bias-correction and for 95% confidence-interval (C. I.) estimation. Sub-sample size

[8] The list of the countries can be found in table 3.

for each country l is given as $m_l = n_l^{0.7}$, n_l is the number of banks in country l. Weights are observed total loans of banks. Standard deviation and confidence-intervals are reported for the weighted mean.

[Tables 3 here]

As can be seen from the table, the efficiency scores vary across countries. The scores range from 0.35 (Albania) to 0.94 (Switzerland) with a mean 0.765. At the first glance, we can see that the banks are relatively more efficient in more developed countries such as U.S., the U.K., Germany, France and Switzerland; while the banks are relatively inefficient in less developed countries such as Albania, Ghana, Lithuania, Nigeria and Philippines. Therefore, we will control for the GDP per capita in our regression analysis to isolate the impact of banking competition and information sharing on bank efficiency.

4.3. Competition

A key independent variable in our study is a measure of banking competition. A widely used measure in this regard is the concentration ratio (e.g., Demirguc-Kunt, Laeven and Levine, 2004). We therefore use the share of the five largest banks in total bank deposits (*Banking Concentration (Deposit)*) from BCL (2006) to measure banking concentration. Higher concentration indicates less competitiveness within the banking industry. As a check on the robustness of the results, we use the share of total assets held by the five largest banks in the industry (*Banking Concentration (Asset)*) as an alternative concentration measure in our analysis. As will be seen, both measures yield very similar and consistent results.

In their survey paper of banking concentration and competition, Berger et al. (2004) point out that bank competition is multifaceted insofar as it encompasses not only bank concentration but also regulatory restrictions, such as entry restrictions and other legal impediments that limit actual and potential bank competition. Thus, we include two additional measures of competition to address this issue. The first variable measures the stringency of entry requirements into the banking industry (*Entry Barrier*). It is a variable constructed on the basis of eight questions regarding whether various types of legal submissions (i.e., draft by-laws, intended organization chart, financial projections for the first three years, financial information on the main potential shareholders, the background of future directors and managers, sources of funds to be disbursed in the capitalization of the new bank and market differentiation intended for the new bank) are required to obtain a banking license. The index ranges from 0 (low entry requirement) to 8 (high entry requirement), with higher values indicating greater stringency. The second variable is the fraction of entry applications denied (*Application Denied*), which is the percentage of applications to enter banking that have been denied in the past five years. This variable varies significantly across countries. At one extreme, the ratio is above 85% in countries like Egypt, Kenya and Pakistan. At the other extreme, the ratio is below 5% in countries like France, Sweden and the United States. All these data are from BCL (2006).

4.4. Information-Sharing

Another key independent variable in our analysis is information sharing. Based on the data available from DMS (2007) and World Bank "Doing Business" dataset, we include two variables to measure information sharing among lenders. Following DMS (2007), the first variable (*Information Sharing*) indicates whether an information sharing agency (public registry or private bureau) exists, which equals one if an information sharing agency is operating in the country by the end of 2005, and zero otherwise. Both public registry and private bureau are database owned by a public authority or private commercial firm, which collect information on the credit worthiness of borrowers and makes it available to financial institutions (DMS, 2007). The depth of credit information, however, varies across countries and regions. Some agencies only collect limited information on outstanding loans of large borrowers, while some other agencies distribute extensive information including late payments and defaults, demographic data, credit inquiries, ratings and sometimes even the payment of utility bills, court records of the company and its owners (Miller, 2003; DMS, 2007). We therefore use the second variable (*Depth of Credit Information*) to capture the difference in information contents across countries. The data is from the World Bank "Doing Business" dataset. Specifically, the depth of credit information index measures rules affecting the scope, accessibility and quality of credit information available through either public or private credit registries. The six characteristics measured by the index include (DMS, 2007): (1) both positive credit information (for example, loan amounts and pattern of on-time repayments) and negative information (for example, late payments, number and amount of defaults and bankruptcies) are distributed; (2) data on both firms and individual borrowers are distributed; (3) data from retailers, trade creditors, or utilities, as well as from financial institutions, are distributed; (4) more than 2 years of historical data are distributed; (5) data are collected on all loans of value above 1% of income per capita; and (6) laws provide for borrowers' right to inspect their own data. A value of one is added to the index when a country's information agencies have each of these characteristics. The index ranges from 0 to 6, with higher values indicating the availability of more credit information, from either a public registry or a private bureau, to facilitate lending decisions.

4.5. Additional Bank Controls

We also control for *Official Supervisory Power, Supervisory Independence, Bank Accounting Disclosure* and *State Owned Bank*. All the variables are from BCL (2006), which were compiled based on a World Bank survey on bank regulation and supervision in 152 countries in year 2003. Official Supervisory Power is constructed from 14 dummy variables that indicate whether bank supervisors can take specific actions against bank management, bank owners, and bank auditors both in normal times and times of distress. This includes information on whether the supervisory agency can force a bank to change its internal organizational structure, suspend dividends, stop bonuses, halt management fees, force banks to constitute provisions against actual or potential losses as determined by the supervisory agency, supersede the legal rights of shareholders, remove and replace managers and directors, obtain information from external auditors, and take legal action against auditors for negligence. On the one hand, supervisory agencies can use these powers to improve the governance of banks as emphasized by the supervisory power view. On the other hand, the supervisory authority can also use these powers to induce banks to allocate credit to favored ends and help achieve the political/economic goals as emphasized by the political/regulatory capture view (Beck, Demirguc-Kunt and Levine, 2006). Therefore, we do not have a clear prediction of the effect of official supervisory power on bank efficiency. The exact definition of *Supervisory Power* is provided in the data appendix. The first principal component indicator of these variables is used. High value indicates wider and stronger authority for bank supervisors.

Supervisory Independence is a dummy variable which measures the degree to which the supervisory authority is protected by the legal system from the banking industry. Specifically, the variable equals one if the supervisors are not legally liable for their actions (i.e. if a supervisor takes actions against a bank, the supervisor can not be sued), and zero otherwise. *Bank Accounting Disclosure* measures whether the income statement includes accrued or unpaid interest or principal on performing and nonperforming loans and whether banks are required to produce consolidated financial statements. A higher value indicates more informative bank financial statements. We expect the *Supervisory Independence* and *Bank Accounting Disclosure* to be positively associated with bank efficiency.

Private and foreign ownership in the banking sector may enhance bank efficiency due to a greater motivation in shaping appropriate managerial incentives, introducing more competition and maintaining a good reputation. By contrast, Sapienza (2004), Khwaja and Mian (2005), and La Porta et al. (2002) argue that state-owned banks[9] are controlled by politicians who use the banks to maximize their own political and personal objectives such as providing jobs for political supporters and bailing out poorly performing state-owned enterprises (SOEs). Existing studies also provide evidence on the distortions in state-owned banks' lending practices (see, for example, Sapienza, 2004, Dinc, 2005).We therefore include one variable to measure the ownership structure of the banking industry. *State Owned Bank* is the fraction of the banking system's assets in banks that are 50% or more owned by government. We expect that the state ownership of banking sector is negatively associated with bank efficiency.

We also control for *Bank size* and *Bank equity*. *Bank size* equals the logarithm of total

[9] According to La Porta et al. (2002), state ownership of banks is common in countries other than the United States. Based on the 10 largest banks in 92 countries, they documented that 42% of their assets are controlled by the state-owned banks.

bank assets in millions of U.S. dollars. Size may be an important determinant of bank efficiency if there is increasing returns to scale in banking. Bank equity is the ratio of the book value of equity to total assets. It is argued that well-capitalized banks face lower bankruptcy costs, and hence lower funding costs and higher bank efficiency (Demirguc-Kunt, Laeven and Levine 2004). We therefore expect that both bank size and bank equity are positively associated with bank efficiency.

4.6. Country Controls

The empirical analysis also includes several country-level variables to control for differences in economic development and institutions across countries. First, we include GDP per capita to capture the economic development of the region/country. Second, we include the natural logarithm of GDP to capture the size of the economy. We also control for the inflation of the economy. Furthermore, we include a series of other political and institutional quality indexes as a check on the robustness of the results. The World Governance Indexes (Kaufmann et al., 2006) are constructed from 276 individual variables taken from 31 different sources produced by 25 different organizations. The indexes measure different dimensions of governance, which can be summarized as follows:

(1) *Government effectiveness (Government Effective)* – the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies.

(2) *Political stability and absence of violence (Political Stability)* – perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including political violence and terrorism.

(3) *Regulatory quality (Regulation)* – the ability of the government to formulate and implement sound policies and regulations that permit and promote market competition and private-sector development.

(4) *Rule of law (LAW)* – the extent to which agents have confidence in and abide by the rules of society, and in particular, the quality of contract enforcement, the police, and the courts, as

well as the likelihood of crime and violence.

(5) *Voice and accountability (Voice)* – the extent to which a country's citizens are able to participate in selecting their government, as well as the extent to which they enjoy freedom of expression, freedom of association, and a free media.

(6) Control of Corruption (*Control of Corruption*) - the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Higher values indicate better control of corruption.

We expect that banks tend to be more efficient in more developed countries and in countries with high quality institutions.

5. Empirical Results

5.1. Information sharing, competition and bank efficiency

Using the bootstrapping DEA method described in section 3, we regress the bank efficiency measure on information sharing, bank competition, and other control variables. The estimation results are presented in table 4. The magnitude of the truncated regression coefficients cannot be simply interpreted as the marginal effects of a one-unit increase in the independent variables on the dependent variable, although the sign and statistical significance of the coefficients are similar to the linear regression interpretations. In order to get some sense of the magnitude of the effects, the coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy variable is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

[Table 4 here]

In Table 4, the most important finding is that banking competition and information sharing increase bank efficiency. As can be seen in the table, the existence of an information sharing credit agency significantly increases bank efficiency, as indicated by the positive and statistically significant coefficients (at the 1% level) of *Information Sharing* in all model specifications. Specifically, the existence of the information sharing credit agency will increase the bank efficiency by 15% to 20%. In addition, the coefficients of *Depth of Credit Information* are positive and statistically significant at the 1% level in all model specifications, suggesting that more credit information shared would lead to higher bank efficiency. Specifically, one unit increase in the *Depth of Credit Information* index (ranges from 0 to 6) is associated with 5%-6% increase in bank efficiency. All these results strongly support our hypothesis 2 that information sharing mechanisms enhance bank efficiency.

The coefficients of *Bank Concentration (Deposit)* and *Bank Concentration (Asset)* are negative and statistically significant at the 1% level in most model specifications, suggesting that increased concentration (i.e., less competitiveness) results in a more severe problem of bank inefficiency. Specifically, a 10% increase in bank concentration reduces the bank efficiency by 0.25% to 0.4%. The coefficients of *Entry Barrier* and *Application Denied* are negative and statistically significant at the 5% level or less in all model specifications. All these results strongly support our theoretical hypothesis 1.A. and 1.B. that higher banking concentration, higher entry barriers and more stringent entry restrictions are associated with lower bank efficiency.

Regarding the bank control variables, the coefficients of *Supervisory Independence* are positive and statistically significant at the 1% level across all models, indicating the importance of an independent supervisor in enhancing bank efficiency. Consistent with our expectation, better bank information disclosure is associated with higher bank efficiency, as indicated by the positive and statistically significant coefficients of *Bank Accounting Disclosure* across model specifications. State ownership of banking sector, as we expected, is negatively associated with bank efficiency. In addition, the *Bank size* is positively associated with bank efficiency, suggesting the existence of increasing return to scale in the banking sector. The *Bank equity*, as we expected, is positively associated with bank efficiency. With respect to the other macro controls, GDP per capita is positively associated with bank efficiency at the significance level 1% across models, indicating the importance of economic development on bank efficiency. The inflation is negatively associated with bank efficiency and the GDP (proxy of country size) is positively associated with bank efficiency. The pseudo R square is about 24%, suggesting a good fitness of the models.

5.2. The impact of information sharing on competition and efficiency

As we discussed earlier in the hypothesis development part, information sharing mechanisms could also encourage a more competitive loan market because information sharing among banks may reduce the informational rents that banks can extract from their clients within lending relationships. The exchange of information among banks can reduce or even eliminate the informational advantage of banks who owns more private information and consequently increase banking competition and bank efficiency. In our empirical results, we expect that the presence of good information sharing mechanisms will attenuate the negative effect of bank concentration and bank entry barriers on bank efficiency. We therefore split the sample into countries with information sharing credit agency (or with high quality information content) and without information sharing credit agency (without high quality information content) and explore the impact of banking concentration and entry barrier on bank efficiency in each sub-sample[10]. The countries with high quality information content are the countries with *Depth of Credit Information* greater than or equal to 3 (the index ranges from 0 to 6). The countries with low quality information content are the countries with *Depth of Credit Information* less than or equal to 2. The empirical results are presented in table 5. Again, the coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy variable is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

[Table 5 here]

As can be seen from the table, the impacts of bank concentration and entry barrier on

[10] We adopt the split-sample approach to separate the effects of the quality of information sharing mechanisms. An alternative approach is to introduce interaction terms by dummy variables. However, the recent econometric literature point out some complications in the interpretation of the interaction term in the limited dependent variable regressions such as our truncated model (e.g., Ai and Norton, 2003). Therefore, the split-sample approach is preferred to present the clear-cut interpretations and to avoid those econometric complications.

corruption are quite different in countries with/without good information sharing mechanisms. Although higher banking concentration, higher entry barriers and more stringent entry restrictions are significantly associated with lower bank efficiency in both sub-samples, the magnitude differs substantially. Specifically, in the countries without good information sharing mechanisms, the impacts of banking concentration, entry barriers and entry restrictions on bank efficiency are triple, quadruple or even more than those in countries with good information sharing mechanisms. For instance, the impact of banking concentration on bank efficiency in countries without high quality information content (b=-0.086) is more than 6 times of that in countries with high quality information sharing (b=-0.0141). Using the Chi-Square test, we find the differences between competition measures in countries with/without good information sharing mechanisms statistically significant. The evidence provide strong support to our hypothesis 3 that information sharing among lenders also improves bank efficiency through its attenuating effect on the impact of bank concentration and entry barrier on bank efficiency.

5.3. Robustness Tests-More Macro Controls

Next, we address the issue of potential omitted variables. Since the overall quality of the institutional environment might influence bank efficiency, we include a series of macro-institutional indexes in our model to test the robustness of the results. Specifically, we include the six components of World Governance Indexes (Kaufmann et al., 2006) to capture different aspects of the institutional environment (control of corruption, political stability, government effectiveness, quality of regulation, voice and accountability, and rule of law). The detailed definition of the indexes can be found in section 4. Because some indexes are highly correlated with each other, we include the indexes individually in the models. The results are presented in Table 6. The estimation is based on bootstrapping DEA method developed by Simar and Wilson (2007). Again, the coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy variable is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

[Table 6 here]

As can be seen from the table, the empirical findings about banking competition and information sharing are very robust to the inclusion of other institutional variables. The competition and information-sharing variables are significantly and positively associated with bank efficiency. Regarding the institutional controls, *Rule of Law* and *Quality of Regulation* are found to exert significant and positive impact on bank efficiency. The *Control of Corruption* has marginally significant and positive impact on bank efficiency. The coefficients of the other institutional variables are not statistically significant though the signs are positive.

5.4. Robustness Tests-Instrumental Variable Analysis

In our study, the potential for endogeneity problem is less of a concern than in pure cross-country analysis because we are examining the impact of competition environment of banking and the existence of information-sharing institutions on individual bank firms. It is unlikely that these firm-based measures of performance will affect the competition environment and institutions. Furthermore, among the countries with information-sharing schemes, more than 85% of them set up the schemes 5 or more years prior to our sample period.

Nevertheless, we conduct some robustness tests using instrumental variable truncated regression analysis. The empirical results are presented in Table 7.

[Table 7 here]

We base the selection of instrumental variables on the theoretical and empirical work in the law, institution and finance literature (Acemoglu and Johnson, 2005, BDL, 2003, Easterly and Levine, 1997, LLSV, 1998, 1999). From the law and finance perspective, LLSV (1999) and BDL (2003) show that the historically determined differences in legal traditions help explain international differences in financial systems today. DMS (2007) find a pronounced legal origin effect in credit market institutions. Moreover, legal origin can be thought of as "exogenous" because it was imposed by colonial power in many emerging countries

(Acemoglu and Johnson, 2005; LLSV, 1999). Furthermore, the legal origin itself is unlikely to have a direct impact on banking performance and activities. Instead, it may exert an indirect impact through the channels of various institutions and regulations. We therefore include legal origin (English, French) as instrumental variables for the banking competition measures using data from DMS (2007). The English legal origin includes the common law of England and its former colonies. The French legal origin includes the civil law of France, of countries Napoleon conquered, and of their former colonies. The endowment theory, on the other hand, focuses on the roles of geography and the disease environment in shaping the political and financial institutional development (Acemoglu et al., 2001, Beck et al., 2003). Beck et al. (2003) find strong evidence that geographical endowment has substantial impacts on the formation of long-lasting institutions that shape financial development. We therefore follow BDL (2005, 2006) in using latitude[11] as an instrumental variable for the competition and information-sharing measures[12]. We also include the ethnic fractionalization[13] as an instrumental variable because it has been found that economies with greater ethnic diversity tend to choose institutions that allow those in power to expropriate resources from others (BDL 2003, 2006). Lastly, it is also reported that a country's culture heritage, as proxied by religion composition, has a significant impact on shaping its political and financial institutions (LLSV, 1999, Stulz and Williamson, 2003).

As can be seen from the table, the empirical results are rather robust. The coefficients of *Information Sharing* and *Depth of Credit Information* remain positive and statistically significant. The results confirm our finding that information sharing mechanisms enhance bank efficiency. Similarly, the coefficients of *Banking Concentration* remain positive and statistically significant in all model specifications, indicating that banking competition improves bank efficiency. The coefficients of *Entry Barrier* and *Application Denied* are also positive and statistically significant across the model specifications. All these results bolster our finding that banking competition, in terms of lowering concentration, lowering entry barriers and imposing less stringent entry restrictions, is associated with higher bank

[11] The absolute value of the latitude of the country, scaled to take a value between 0 and 1, is from LLSV (1999).
[12] We did not use the mortality ratio proposed by Acemoglu and Johnson (2001) because it has a small overlap in countries with the sample we are using.
[13] We use the average value of five different indices of ethnical fractionalization. The data are from Easterly and Levine (1997).

efficiency.

As can be also seen from the table, the impacts of bank concentration and entry barrier on corruption are quite different in countries with/without good information sharing mechanisms after handling the potential endogeneity problem. Although higher banking concentration, higher entry barriers and more stringent entry restrictions are significantly associated with lower bank efficiency in both sub-samples, the magnitude differs substantially. Specifically, in the countries without good information sharing mechanisms, the impacts of banking concentration, entry barriers and entry restrictions on bank efficiency are triple, quadruple or even more than those in countries with good information sharing mechanisms. Using the Chi-Square test, we find the differences between competition measures in countries with/without good information sharing mechanisms statistically significant. The evidence confirms our previous finding that information sharing among lenders also improves bank efficiency through its attenuating effect on the impact of bank concentration and entry barrier on bank efficiency.

Regarding the control variables, the state ownership of the banking industry are negatively associated with bank efficiency. The bank information disclosure and supervisory independence enhance bank efficiency, as indicated by the positive and statistically significant coefficients across model specifications. Overall, the results are very consistent with our previous findings and predictions.

5.5. Robustness Tests: Estimation Based on Three-Year Average

We test the robustness of the results using data over the 2004-2006 period. One advantage of using data averaged over the 2004-2006 period is that we smooth variables that vary over time (Demirguc-Kunt et al. 2004). Both the inputs/outputs data in estimating bank efficiency scores and the independent variables are the three year average data from 2004 to 2006. The banking regulation variables are time invariant because they are based on the survey in 2003. The empirical results are presented in table 8.

[Table 8 here]

As can be seen from table 8, the results are highly robust to our previous findings.

5.6. Further Exploration-Sample Splits

Based on our previous results, we find that better rule of law is associated with higher bank efficiency. We then split the sample into countries with better rule of law (the countries with rule of law scores above the sample median) and poor rule of law(the countries with rule of law scores above the sample median) and explore the impacts of banking competition and information sharing on corruption in lending in each sub-sample. In addition, we split the sample into countries with more developed (OECD countries plus Hong Kong and South Korea) and less developed (the other countries in the sample) and repeat the analysis. The empirical results are presented in table 9.

[Table 9 here]

In Table 9, it is clear that both information sharing variables have much less impact on bank efficiency in countries with good rules of law than those countries with poor rule of law. These results suggest that, to some extent, information sharing mechanisms serve as substitute for good rule of law. Bank concentration measure has less negative impact on bank efficiency in countries with good rule of law, suggesting that in these countries, bank concentration may not be a good measure of bank competition (also see Demiguc-Kunt et al 2004). The effect of *Entry Barrier* and *Application Denied*, however, are similar across the two types of countries. Similarly, in countries with high income, the effect of information sharing is much less than that in low income countries, suggesting credit information sharing works more effectively in low income countries in enhancing bank efficiency. Bank concentration also has less negative impact on more developed countries, again similar to those findings in Demiguc-Kunt et al (2004). There is not much difference in the effect of entry barriers and application denied on bank efficiency across high and low income countries.

6. Conclusion

Our paper examines whether bank competition and information sharing help improve bank efficiency. We use three unique datasets: (1) the BankScope database provided by Bureau van Dijk and Fitch Ratings, (2) Barth, Caprio, and Levine (2006) dataset on bank supervision and regulation in 152 countries, (3) and the Djankov, McLiesh, and Schleifer (DMS henceforth) (2007) and World Bank "Doing Business" dataset on information sharing in 178 countries. The final sample includes about 1200 banks in 69 countries.

Using the state-of-the-art nonparametric double bootstrapping DEA approach, we find that information sharing and banking competition enhance the bank efficiency. Moreover, information sharing attenuates the negative effects of bank concentration and entry barriers on bank efficiency. We also find that larger banks and highly capitalized banks are generally associated with more bank efficiency. Finally, more developed countries with less inflation are usually associated with higher bank efficiency. Our findings are robust to controlling for different banking, macroeconomic, regulatory, and institutional factors and several endogeneity tests.

We contribute to the literature as follows. First, our DEA method is the state-of-the-art technique in the literature. It provides a comprehensive multi-dimension measure of the bank efficiency and can cope with the random errors and estimation bias problems that the traditional DEA approach could not deal with. Second, our paper is the first to examine a broad measure of bank competition and information sharing on the DEA efficiency. Our sample covers a large number of developed, developing, and transition countries. The wider variations in market structure, information sharing mechanisms, and macro-economic conditions across countries allow us to study, with greater statistical power, their impact on banking firm efficiency. Third, we contribute to the small but growing literature on the role of information sharing among lenders in credit market development. To our knowledge, this paper is the first empirical study on the impact of information sharing on bank efficiency and its interaction effect with bank industry on bank efficiency. Our paper adds to the information sharing literature by finding evidence that information sharing improves bank efficiency and attenuates the effect of banking concentration and entry barrier on bank efficiency.

Although the institution and macro-economic variables that have been identified in this paper are out of control of the bank management, they still help us to isolate these institutional/environment factors on bank efficiency. To some extent, the governments in different countries are able to encourage bank competition by reducing entry barriers and promoting information sharing through public/private credit registries. Our results suggest that these efforts shall help banks to achieve higher efficiency.

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Table 1: Variable definitions and data sources

Variable	Definition	Original Sources
Outputs of Banks		
Total Loans	Loans + total other lending (mil USD)	BankScope
Other Earning Assets	Total other earning assets (mil USD)	BankScope
Other Operating Income	Other operating income (mil USD)	BankScope
Inputs of Banks		
Total Deposits	Total deposits + total money market funding + total other funding (mil USD)	BankScope
Labor Input	Personnel expenses (mil USD)	BankScope
Capital Input	Fixed assets (mil USD)	BankScope
Bank Efficiency	Technical efficiency of the bank	Authors' calculation
Bank Size	Natural logarithm of total assets	BankScope
Bank Equity	The book value of equity divided by total assets	BankScope
Bank Concentration (Deposit)	The fraction of total deposits held by the five largest banks in the industry. The data are compiled based on a survey of banking regulators in 150 countries in 2001.	Barth et al. (2006)
Bank Concentration (Asset)	The fraction of total assets held by the five largest banks in the industry. The data are compiled based on a survey of banking regulators in 150 countries in 2001.	Barth et al. (2006)
Entry Barrier	Entry into Banking Requirement, which is a variable developed based on eight questions regarding whether various types of legal submission are required to obtain a banking license. Which of the following are legally required to be submitted before issuance of the banking license? (1)Draft by-laws? (2)Intended organization chart? (3) Financial projections for first three years? (4) Financial information on main potential shareholders? (5) Background/experience of future directors? (6) Background/experience of future managers? (7) Sources of funds to be disbursed in the capitalization of new bank? (8) Market differentiation intended for the new bank? The index ranges from 0 (low entry requirement) to 8 (high entry requirement). Higher values indicate greater stringency	Barth et al. (2006)

Application Denied	The percentage to which applications to enter banking are denied in the past five years. The data are compiled based on a survey of banking regulators in 150 countries in 2001.	Barth et al. (2006)
State Owned Bank	The fraction of the banking system's assets in the banks that are 50 percent or more owned by government. The data are compiled based on a survey of banking regulators in 150 countries in 2003.	Barth et al. (2006)
Information Sharing	The variable equals one if an information sharing agency (public registry or private bureau) operates in the country by the end of 2005, zero otherwise.	Djankov et al. (2007), World Bank "Doing Business" databse
Depth of Credit Information	An index measures the information contents of the credit information. A value of one is added to the index when a country's information agencies have each of these characteristics: (1) both positive credit information (for example, loan amounts and pattern of on-time repayments) and negative information (for example, late payments, number and amount of defaults and bankruptcies) are distributed; (2) data on both firms and individual borrowers are distributed; (3) data from retailers, trade creditors, or utilities, as well as from financial institutions, are distributed; (4) more than 2 years of historical data are distributed; (5) data are collected on all loans of value above 1% of income per capita; and (6) laws provide for borrowers' right to inspect their own data. The index ranges from 0 to 6, with higher values indicating the availability of more credit information, from either a public registry or a private bureau, to facilitate lending decisions.	Djankov et al. (2007), World Bank "Doing Business" databse
Bank Accounting	Whether the income statement includes accrued or unpaid interest or principal on performing and nonperforming loans and whether banks are required to produce consolidated financial statements. Higher value indicates more informative bank account.	Barth et al. (2006)
Official Supervisory Power	Principal component indicator of 14 dummy variables: 1.Does the supervisory agency have the right to meet with external auditors to discuss their report without the approval of the bank? 2.Are auditors required by law to communicate directly to the supervisory agency any presumed involvement of bank directors or senior managers in elicit activities, fraud, or insider abuse? 3. Can supervisors take legal action against external auditors for negligence? 4.Can the supervisory authority force a bank to change its internal organizational structure? 5. Are off-balance sheet items disclosed to supervisors? 6. Can the supervisory agency order the bank's directors or management to	Barth et al. (2006)

	constitute provisions to cover actual or potential losses? 7. Can the supervisory agency suspend the directors' decision to distribute: a) Dividends? b) Bonuses? c) Management fees? 8. Can the supervisory agency legally declare-such that this declaration supersedes the rights of bank shareholders-that a bank is insolvent? 9. Does the Banking Law give authority to the supervisory agency to intervene that is, suspend some or all ownership rights-a problem bank? 10.Regarding bank restructuring and reorganization, can the supervisory agency or any other government agency do the following: a) Supersede shareholder rights? b) Remove and replace management? c) Remove and replace directors?	
Supervisory Independence	The degree to which the supervisory authority is protected by the legal system from the baking industry. The variable equals one if the supervisors are not legally liable for their actions (i.e. if a supervisor takes actions against a bank, the supervisor can not be sued), and zero otherwise.	Barth et al. (2006)
Inflation	3-year average percentage inflation, GDP deflator.	World Development Indicators (WDI)
GDP per Capita	Logarithm of gross domestic product per capita in year 2006.	World Development Indicators (WDI)
GDP	Natural logarithm of gross domestic product in year 2006.	World Development Indicators (WDI)
Voice and Accountability	The indicator measures the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and free media. The value of year 2005 is used in this study. Higher values mean greater political rights.	Kaufmann et al. (2006)
Government Effectiveness	The indicator measures the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. The value of year 2005 is used in this study. Higher values mean higher quality of public and civil service.	Kaufmann et al. (2006)
Rule of Law	The indicator measures the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence. The value of year 2005 is used in this study. Higher values mean stronger law and order.	Kaufmann et al. (2006)

Political Stability	The indicator measures the perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including political violence and terrorism. The value of year 2005 is used in this study. Higher values mean more stable political environment.	Kaufmann et al. (2006)
Quality of Regulation	The indicator measures the ability of the government to formulate and implement sound policies and regulations that permit and promote market competition and private-sector development. The value of year 2005 is used in this study. Higher values mean higher quality of regulation.	Kaufmann et al. (2006)
Control of Corruption	The indicator measures the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. The value of year 2005 is used in this study. Higher values indicate better control of corruption.	Kaufmann et al. (2006)

Table 2: Summary statistics

Variable	Mean	Median	SD	No. of banks
Panel A: Bank level data				
Outputs of banks				
Total loans	6.0	6.2	3.0	1181
Other earning assets	5.4	5.3	2.9	1181
Other operating incomes	2.7	2.4	2.6	1181
Inputs of banks				
Total deposit	6.5	6.6	2.9	1181
Labor input	2.6	2.5	2.5	1181
Capital input	2.4	2.4	2.6	1181
Bank characteristics				
Bank size	6.7	6.7	2.9	1181
Bank equity	11.9	10.0	7.3	1181
Panel B: Banking Sector Variables				No. of countries
Information Sharing	0.9	1.0	0.3	69
Depth of Credit Information	4.0	5.0	1.9	69
Banking Competition Variables				
Bank Concentration (Assets)	0.7	0.7	0.2	67
Bank Concentration (Deposits)	0.7	0.7	0.2	67
Entry Barrier	7.4	8.0	1.0	69
Application Denied	16.0	3.3	24.6	55
Control variables				
Official Supervisory Power	10.7	11.0	2.3	69
Bank Accounting Disclosure	3.7	4.0	0.5	69
Supervisory Independence	0.6	1.0	0.5	69
State Owned Bank	14.5	5.1	19.5	69
Panel C: Other Control Variables				
Inflation	4.5	3.0	4.4	69
GDP per Capita	9.1	9.1	1.3	69
GDP	25.5	25.6	1.8	69
Control of Corruption	0.5	0.3	1.1	69
Government Effectiveness	0.6	0.7	1.0	69
Political Stability	0.2	0.3	0.9	69
Quality of Regulation	0.6	0.8	0.9	69
Rule of Law	0.5	0.5	1.0	69

Note: See Table 1 for variable definitions. SD denotes standard deviation. Panel A is bank level data. Panel B and C are the country level data.

Table 3: Banking Efficiency Score across Countries

Country name	Mean (unweighted)	Weighted mean (by total loans)	Standard Deviation	95% C. I. lower bound	95% C. I. upper bound
ALBANIA	0.357	0.356	0.017	0.323	0.380
ARGENTINA	0.686	0.685	0.056	0.584	0.762
AUSTRALIA	0.758	0.768	0.015	0.712	0.773
AUSTRIA	0.843	0.863	0.032	0.789	0.892
AZERBAIJAN	0.507	0.508	0.029	0.459	0.551
BELARUS	0.691	0.691	0.030	0.647	0.761
BELGIUM	0.936	0.936	0.010	0.913	0.955
BOLIVIA	0.606	0.579	0.020	0.541	0.613
BOTSWANA	0.733	0.673	0.091	0.546	0.866
BRAZIL	0.748	0.793	0.017	0.738	0.807
BULGARIA	0.589	0.628	0.071	0.497	0.711
CANADA	0.913	0.923	0.015	0.887	0.932
CHILE	0.737	0.741	0.044	0.698	0.844
COLOMBIA	0.574	0.593	0.032	0.535	0.639
COSTA RICA	0.613	0.617	0.036	0.546	0.711
CZECH REPUBLIC	0.648	0.648	0.012	0.646	0.656
DENMARK	0.790	0.820	0.030	0.765	0.855
ECUADOR	0.544	0.531	0.030	0.484	0.588
EL SALVADOR	0.597	0.643	0.033	0.562	0.715
ESTONIA	0.591	0.591	0.041	0.533	0.657
FINLAND	0.909	0.912	0.017	0.849	0.921
FRANCE	0.906	0.920	0.016	0.874	0.930
GERMANY	0.899	0.922	0.027	0.847	0.944
GHANA	0.532	0.533	0.020	0.498	0.565
GREECE	0.725	0.728	0.032	0.669	0.779
GUYANA	0.534	0.534	0.027	0.492	0.592
HONDURAS	0.575	0.559	0.031	0.502	0.623
HONG KONG	0.813	0.831	0.023	0.765	0.852
HUNGARY	0.806	0.806	0.036	0.755	0.853
ICELAND	0.926	0.925	0.011	0.891	0.931
INDIA	0.690	0.733	0.038	0.674	0.794
ITALY	0.860	0.868	0.011	0.835	0.876
JAPAN	0.821	0.853	0.046	0.771	0.902
KAZAKHSTAN	0.564	0.615	0.049	0.550	0.695
KENYA	0.578	0.592	0.035	0.511	0.653
KOREA REP. OF	0.863	0.863	0.037	0.807	0.901
LATVIA	0.514	0.542	0.041	0.422	0.599
LITHUANIA	0.435	0.470	0.120	0.211	0.591
LUXEMBOURG	0.912	0.919	0.013	0.896	0.922
MACAU	0.789	0.789	0.020	0.762	0.832
MACEDONIA (FYROM)	0.745	0.745	0.021	0.711	0.788
MALAYSIA	0.701	0.708	0.012	0.676	0.721
MAURITIUS	0.788	0.825	0.048	0.709	0.909

MOROCCO	0.608	0.608	0.036	0.574	0.749
NETHERLANDS	0.666	0.679	0.048	0.587	0.730
NEW ZEALAND	0.705	0.712	0.011	0.705	0.713
NIGERIA	0.446	0.456	0.024	0.406	0.495
NORWAY	0.903	0.903	0.002	0.896	0.904
PAKISTAN	0.515	0.553	0.027	0.516	0.620
PANAMA	0.690	0.718	0.039	0.632	0.769
PERU	0.555	0.536	0.048	0.463	0.650
PHILIPPINES	0.472	0.471	0.048	0.386	0.554
POLAND	0.549	0.555	0.040	0.470	0.612
PORTUGAL	0.874	0.874	0.027	0.806	0.891
ROMANIA	0.610	0.604	0.042	0.533	0.676
RUSSIAN FEDERATION	0.787	0.799	0.044	0.727	0.873
SINGAPORE	0.862	0.861	0.034	0.789	0.886
SLOVENIA	0.667	0.667	0.008	0.657	0.674
SOUTH AFRICA	0.727	0.805	0.054	0.697	0.835
SPAIN	0.931	0.936	0.011	0.905	0.940
SWEDEN	0.806	0.805	0.015	0.754	0.810
SWITZERLAND	0.940	0.939	0.052	0.756	0.963
THAILAND	0.736	0.763	0.033	0.688	0.810
TRINIDAD AND TOBAGO	0.650	0.656	0.049	0.598	0.773
TURKEY	0.710	0.746	0.056	0.641	0.806
UKRAINE	0.649	0.651	0.015	0.621	0.674
UNITED KINGDOM	0.902	0.931	0.026	0.871	0.951
USA	0.858	0.924	0.021	0.877	0.949
VENEZUELA	0.406	0.412	0.051	0.336	0.527
ALL	0.765	0.792	0.034	0.727	0.843

Note: A three-input and three-output financial intermediation model is constructed to measure the bank efficiency scores (see section 3 and 4.2 for details). Estimation of weighted mean is based on Simar and Zelenyuk (2007) group-wise heterogeneous sub-sampling procedure, with 2,000 bootstrap replications both for bias-correction and for 95% confidence-interval (C. I.) estimation. Sub-sample size for each country l is given as $m_l = n_l^{0.7}$, n_l is the number of banks in country l. Weights are observed total loans of banks. Standard deviation and confidence-intervals are for the weighted mean.

Table 4: Information sharing, competition, and bank efficiency

	(1)	(2)	(3)	(4)	(5)	(6)
Information Sharing	0.1277			0.1311	0.1368	0.1454
	[0.002]***			[0.002]***	[0.002]***	[0.001]***
Depth of Credit Information	0.0585			0.0534	0.0525	0.054
	[0.008]***			[0.014]**	[0.011]**	[0.010]***
Bank Concentration (Asset)		-0.0285		-0.0239	-0.0237	
		[0.006]***		[0.040]**	[0.043]**	
Bank Concentration (Deposit)			-0.0305			-0.028
			[0.012]**			[0.023]**
Entry Barrier		-0.0206	-0.0176	-0.0204	-0.0251	-0.0209
		[0.018]**	[0.036]**	[0.014]**	[0.011]**	[0.035]**
Application Denied		-0.0182	-0.0181		-0.0192	-0.0187
		[0.026]**	[0.024]**		[0.037]**	[0.039]**
Control Variables						
Official Supervisory Power	0.018	0.016	0.0163	0.0182	0.0167	0.0162
	[0.091]*	[0.232]	[0.208]	[0.076]*	[0.220]	[0.235]
Supervisory Independence	0.0221	0.0227	0.0235	0.0202	0.0201	0.02
	[0.009]***	[0.006]***	[0.008]***	[0.012]**	[0.017]**	[0.014]**
Bank Accounting Disclosure	0.0211	0.019	0.0217	0.0219	0.0193	0.0219
	[0.026]**	[0.066]*	[0.039]**	[0.030]**	[0.037]**	[0.035]**
State Owned Banks	-0.0038	-0.0039	-0.0033	-0.0043	-0.0036	-0.0031
	[0.038]**	[0.035]**	[0.080]*	[0.028]**	[0.044]**	[0.054]*
Bank Size	0.067	0.0711	0.0723	0.082	0.072	0.07
	[0.052]*	[0.037]**	[0.035]**	[0.008]***	[0.045]**	[0.054]*
Bank Equity	0.0062	0.0064	0.0064	0.0058	0.0075	0.0069
	[0.026]**	[0.027]**	[0.023]**	[0.058]*	[0.036]**	[0.045]**
Inflation	-0.0012	-0.0019	-0.0018	-0.0012	-0.0018	-0.0011
	[0.043]**	[0.037]**	[0.045]**	[0.041]**	[0.032]**	[0.078]*
GDP per Capita	0.006	0.0058	0.0058	0.0059	0.0059	0.0057
	[0.026]**	[0.029]**	[0.030]**	[0.031]**	[0.030]**	[0.032]**
GDP	0.0063	0.0053	0.0068	0.0065	0.0063	0.0075
	[0.031]**	[0.138]	[0.018]**	[0.037]**	[0.034]**	[0.021]**
Constant	0.3112	0.3293	0.264	0.313	0.2927	0.257
	[0.026]**	[0.044]**	[0.076]*	[0.047]**	[0.064]*	[0.069]*
Pseudo R2	0.239	0.224	0.226	0.227	0.231	0.231
Log likelihood	1208.109	945.77	947.65	1190.15	953.66	954.52
Observations	1181	1005	1005	1173	1005	1005

Note: See Table 1 for variable definitions. The estimation is based on bootstrapping DEA method developed by Simar and Wilson (2007). *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively. The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy variable is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

Table 5: Split sample estimations according to the level and quality of information sharing

	With Information Sharing	No Information Sharing	High Quality Information Content	Low Quality Information Content
	(1)	(2)	(3)	(4)
Bank Concentration (Asset)	-0.0182	-0.0563	-0.0128	-0.0671
	[0.024]**	[0.036]**	[0.039]**	[0.006]***
Entry Barrier	-0.0145	-0.0542	-0.0129	-0.0373
	[0.039]**	[0.033]**	[0.040]**	[0.018]**
Application Denied	-0.0112	-0.045	-0.016	-0.05
	[0.031]**	[0.001]***	[0.025]**	[0.013]**
Control Variables				
Official Supervisory Power	0.0252	0.0128	0.0366	0.0152
	[0.114]	[0.141]	[0.126]	[0.187]
Supervisory Independence	0.0213	0.017	0.0218	0.0184
	[0.049]**	[0.047]**	[0.008]***	[0.035]**
Bank Accounting Disclosure	0.0257	0.0215	0.0261	0.0225
	[0.011]**	[0.031]**	[0.002]***	[0.012]**
State Owned Banks	-0.0034	-0.0039	-0.0031	-0.0035
	[0.067]*	[0.042]**	[0.634]	[0.032]**
Bank Size	0.0864	0.0654	0.0922	0.0743
	[0.032]**	[0.041]**	[0.028]**	[0.008]***
Bank Equity	0.0052	0.0071	0.0053	0.0083
	[0.017]**	[0.015]**	[0.012]**	[0.013]**
Inflation	-0.0025	-0.0037	-0.0033	-0.0131
	[0.169]	[0.001]***	[0.077]*	[0.004]**
GDP per Capita	0.0071	0.0063	0.0084	0.0064
	[0.034]**	[0.029]**	[0.036]**	[0.041]**
GDP	0.0082	0.0071	0.0084	0.0068
	[0.021]**	[0.073]*	[0.035]**	[0.123]
Constant	0.25	0.2004	0.191	0.2558
	[0.081]*	[0.021]**	[0.074]*	[0.031]**
Pseudo R^2	0.244	0.114	0.223	0.116
Log likelihood	670.71	396.41	635.92	371.57
Observations	596	409	559	446

Note: See Table 1 for variable definitions. Eq. (1) and (2) split the full sample of eq. (5) (1,005 banks in total) in Table 4 according to the dummy variable 'Information Sharing' that equals to one (eq. (1)) or zero (eq. (2)), respectively. Eq. (3) and (4) split the full sample again according to the variable 'Depth of Credit Information'. Since the variable 'Depth of Credit Information' ranges from 0 (no info sharing) to 6 (highest quality of information sharing), 'Depth of Credit Information' ≤ 2 means the quality of information sharing is below the average level 3, which defines the sample for eq. (4). The remaining observations are included in the sample for eq. (3). The coefficients of the three variables related to the degree of competition, 'Bank Concentration (Asset)', 'Entry Barrier', and 'Application Denied', are significantly smaller at the 1% level in countries with information sharing (eq. (1)) and high quality information sharing (eq. (3)) than those in countries with no information sharing (eq. (2)) and with low quality of information sharing (eq. (4)), respectively. The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively.

Table 6: Robustness Tests: More Institutional Controls

	(1)	(2)	(3)	(4)	(5)	(6)
Information Sharing	0.1161	0.1237	0.1212	0.1013	0.1232	0.1581
	[0.005]***	[0.003]***	[0.004]***	[0.007]***	[0.004]***	[0.000]***
Depth of Credit Information	0.0575	0.0581	0.0555	0.0672	0.0657	0.0753
	[0.014]**	[0.015]**	[0.014]**	[0.047]**	[0.014]**	[0.009]***
Bank Concentration (Asset)	-0.0242	-0.0232	-0.0264	-0.0205	-0.0203	-0.0255
	[0.038]**	[0.045]**	[0.026]**	[0.034]**	[0.035]**	[0.027]**
Entry Barrier	-0.0265	-0.0245	-0.0253	-0.0265	-0.0276	-0.0261
	[0.038]**	[0.031]**	[0.038]**	[0.031]**	[0.042]**	[0.036]**
Application Denied	-0.0181	-0.0173	-0.0179	-0.0216	-0.0186	-0.0185
	[0.036]**	[0.035]**	[0.034]**	[0.031]**	[0.032]**	[0.038]**
Control Variables						
Official Supervisory Power	0.0158	0.0186	0.016	0.016	0.0158	0.0186
	[0.243]	[0.093]*	[0.232]	[0.1710]	[0.243]	[0.081]*
Supervisory Independence	0.0203	0.024	0.0211	0.0182	0.0209	0.0224
	[0.015]**	[0.013]**	[0.010]**	[0.017]**	[0.018]**	[0.020]**
Bank Accounting Disclosure	0.0196	0.0176	0.018	0.0195	0.0183	0.0176
	[0.018]**	[0.015]**	[0.020]**	[0.024]**	[0.025]**	[0.017]**
State Owned Bank	-0.0034	-0.0039	-0.004	-0.0038	-0.0036	-0.0039
	[0.044]**	[0.040]**	[0.036]**	[0.031]**	[0.042]**	[0.041]**
Banks Size	0.0711	0.0683	0.0718	0.0673	0.0711	0.0701
	[0.044]**	[0.058]*	[0.033]**	[0.055]*	[0.023]**	[0.029]**
Bank Equity	0.0078	0.0075	0.0069	0.0058	0.0072	0.0074
	[0.046]**	[0.047]**	[0.045]**	[0.043]**	[0.031]**	[0.041]**
Inflation	-0.0018	-0.0014	-0.0018	-0.0017	-0.0013	-0.0019
	[0.042]**	[0.104]	[0.039]**	[0.026]**	[0.051]*	[0.044]**
GDP Per Capita	0.0051	0.0053	0.0055	0.0045	0.0055	0.0062
	[0.049]**	[0.044]**	[0.039]**	[0.036]**	[0.040]**	[0.028]**
GDP	0.0056	0.0063	0.0072	0.0057	0.0056	0.0056
	[0.043]**	[0.038]**	[0.041]**	[0.056]*	[0.038]**	[0.044]**
Control of Corruption	0.0541					
	[0.082]*					
Government Effectiveness		0.0442				
		[0.314]				
Political Stability			0.0312			
			[0.327]			
Quality and Regulation				0.0617		
				[0.030]**		
Rule of Law					0.0264	
					[0.027]**	
Voice and Accountability						0.0328
						[0.311]
Constant	0.3412	0.3322	0.3074	0.384	0.3222	0.2946
	[0.046]**	[0.050]*	[0.062]*	[0.036]**	[0.056]*	[0.075]*
Pseudo R^2	0.232	0.231	0.231	0.236	0.231	0.231

Log likelihood	954.78	954.27	954.11	959.59	953.94	954.23
Observations	1005	1005	1005	1005	1005	1005

Note: Control of Corruption is an indicator which measures the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Higher values indicate better control of corruption. Government Effectiveness is an indicator which measures the quality of public services, the quality of the civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies. Higher values mean higher quality of public and civil service. Political Stability is an indicator which measures the perceptions of the likelihood that the government will be destabilized or overthrown by unconstitutional or violent means, including political violence and terrorism. Higher values mean more stable political environment. Quality of Regulation is an indicator which measures the ability of the government to formulate and implement sound policies and regulations that permit and promote market competition and private-sector development. Higher values mean higher quality of regulation. Rule of Law is an indicator which measures the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence. Higher values mean stronger law and order. Voice and Accountability is an indicator which measures the extent to which a country's citizens are able to participate in selecting their government, as well as freedom of expression, freedom of association, and free media. Higher values mean greater political rights. The other variables are defined as previously. The estimation is based on bootstrapping DEA method developed by Simar and Wilson (2007). *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively. The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy variable is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

Table 7: Robustness tests: Instrumental Variables Estimation Results

	(1)	(2)	(3)	(4)	(5)	(6)
	Full Sample	Full Sample	With Information Sharing	No Information Sharing	High Quality Information Content	Low Quality Information Content
Information Sharing		0.2743				
		[0.000]***				
Depth of Credit Information		0.0957				
		[0.003]***				
Bank Concentration (Asset)	-0.0580	-0.0496	-0.0382	-0.1179	-0.0259	-0.1037
	[0.003]***	[0.006]***	[0.007]***	[0.038]**	[0.005]***	[0.000]***
Entry Barrier	-0.0427	-0.0522	-0.0303	-0.1095	-0.0259	-0.0773
	[0.004]***	[0.001]***	[0.032]**	[0.001]***	[0.079]*	[0.000]***
Application Denied	-0.0376	-0.0402	-0.0225	-0.0920	-0.0332	-0.1032
	[0.011]**	[0.017]**	[0.033]**	[0.000]***	[0.005]***	[0.000]***
Control Variables						
Official Supervisory Power	0.0023	0.0317	0.0514	0.0261	0.0408	0.0306
	[0.543]	[0.207]	[0.104]	[0.134]	[0.138]	[0.126]
Supervisory Independence	0.0386	0.0394	0.0413	0.0349	0.0430	0.0372
	[0.010]***	[0.003]***	[0.019]**	[0.013]**	[0.017]**	[0.000]***
Bank Accounting Disclosure	0.0174	0.0182	0.0480	0.0449	0.0478	0.0455
	[0.058]*	[0.017]**	[0.039]**	[0.000]***	[0.027]**	[0.000]***
State Owned Banks	-0.0081	-0.0076	-0.0030	-0.0082	-0.0041	-0.0060
	[0.017]**	[0.017]**	[0.022]**	[0.000]***	[0.0362]**	[0.000]***
Bank Size	0.0896	0.0802	0.0749	0.0670	0.0865	0.0637
	[0.037]**	[0.045]**	[0.032]**	[0.041]**	[0.028]**	[0.008]***
Bank Equity	0.0039	0.0041	0.0039	0.0045	0.0037	0.0088
	[0.017]**	[0.022]**	[0.040]**	[0.029]**	[0.028]**	[0.013]**
Inflation	-0.0026	-0.0015	-0.0051	-0.0077	-0.0026	-0.0063
	[0.001]***	[0.039]**	[0.073]*	[0.000]***	[0.090]*	[0.000]***
GDP per capita	0.0077	0.0063	0.0085	0.0066	0.0083	0.0066
	[0.040]**	[0.041]**	[0.025]**	[0.000]***	[0.037]**	[0.000]***
GDP	0.0111	0.0082	0.0067	0.0043	0.0073	0.0067
	[0.032]**	[0.021]**	[0.007]***	[0.000]***	[0.002]***	[0.000]***
Constant	0.6595	0.5990	0.5092	0.4040	0.3874	0.1685
	[0.026]**	[0.018]**	[0.058]*	[0.002]***	[0.034]**	[0.000]***
Pseudo R2	0.262	0.273	0.254	0.124	0.232	0.148
Log likelihood	967.04	973.83	659.09	404.50	613.14	436.16
Observations	1005	1005	596	409	559	446

Note: See Table 1 for variable definitions, Table 5 for the definitions of sample split. Instrumental variables include ethnic fractionalization, latitude, religions, and legal origins. *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively. The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

Table 8: Robustness tests: Estimation results based on three-year (2004-2006) average data

	(1)	(2)	(3)	(4)	(5)	(6)
			With Information Sharing	No Information Sharing	High Quality Information Content	Low Quality Information Content
Information Sharing		0.1250				
		[0.001]***				
Depth of Credit Information		0.0430				
		[0.003]***				
Bank Concentration (Asset)	-0.0556	-0.0391	-0.0177	-0.0403	-0.0159	-0.0484
	[0.003]***	[0.014]**	[0.015]**	[0.012]**	[0.028]**	[0.005]***
Entry Barrier	-0.0164	-0.0121	-0.0115	-0.0626	-0.0167	-0.0528
	[0.019]**	[0.012]**	[0.019]**	[0.001]***	[0.042]**	[0.049]**
Application Denied	-0.0257	-0.0322	-0.0149	-0.0598	-0.0249	-0.0625
	[0.008]***	[0.007]***	[0.037]**	[0.011]**	[0.014]**	[0.001]***
Control Variables						
Official Supervisory Power	0.0152	0.0195	0.0434	0.0153	0.0324	0.0109
	[0.280]	[0.231]	[0.140]	[0.153]	[0.138]	[0.202]
Supervisory Independence	0.0172	0.0128	0.0215	0.0161	0.0224	0.0158
	[0.072]*	[0.041]**	[0.015]**	[0.047]**	[0.024]**	[0.004]***
Bank Accounting Disclosure	0.0174	0.0172	0.0160	0.0148	0.0185	0.0181
	[0.005]***	[0.003]***	[0.018]**	[0.008]***	[0.002]***	[0.002]***
State Owned Banks	-0.0027	-0.0022	-0.0026	-0.0027	-0.0022	-0.0025
	[0.049]**	[0.047]**	[0.036]**	[0.037]**	[0.128]	[0.011]**
Bank Size	0.0501	0.0494	0.0568	0.0472	0.0643	0.0524
	[0.037]**	[0.045]**	[0.032]**	[0.041]**	[0.028]**	[0.008]***
Bank Equity	0.0036	0.0042	0.0036	0.0042	0.0047	0.0050
	[0.027]**	[0.036]**	[0.000]***	[0.015]**	[0.000]***	[0.013]**
Inflation	-0.0014	-0.0011	-0.0046	-0.0062	-0.0027	-0.0074
	[0.002]***	[0.002]***	[0.035]**	[0.021]**	[0.073]*	[0.000]***
GDP per capita	0.0068	0.0098	0.0046	0.0033	0.0084	0.0083
	[0.008]***	[0.003]***	[0.045]**	[0.015]**	[0.028]**	[0.001]***
GDP	0.0025	0.0037	0.0033	0.0020	0.0049	0.0045
	[0.190]	[0.031]**	[0.033]**	[0.014]**	[0.030]**	[0.065]*
Constant	0.3337	0.4751	0.2936	0.1467	0.2311	0.1866
	[0.022]**	[0.050]**	[0.038]**	[0.021]**	[0.038]**	[0.024]**
Pseudo R2	0.261	0.261	0.256	0.103	0.225	0.113
Log likelihood	978.25	984.43	605.59	386.05	582.47	357.40
Observations	1005	1005	596	409	559	446

Note: See Table 1 for variable definitions, Table 5 for the definitions of sample split. *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively. The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. The marginal effect of a dummy variable is calculated as the discrete change in the expected value of the dependent variable as the dummy variable changes from 0 to 1.

Table 9: Split sample estimations according to the rule of law and income level

	Countries with good rule of law	Countries with poor rule of law	Countries with high income	Countries with low income
	(1)	(2)	(3)	(4)
Information Sharing	0.0987	0.2732	0.1099	0.2495
	[0.003]***	[0.000]***	[0.008]***	[0.000]***
Depth of Credit Information	0.0301	0.0824	0.0378	0.0724
	[0.013]**	[0.000]***	[0.036]**	[0.000]***
Bank Concentration (Asset)	-0.0270	-0.0489	-0.0114	-0.0246
	[0.047]**	[0.032]**	[0.000]***	[0.043]**
Entry Barrier	-0.0107	-0.0150	-0.0227	-0.0263
	[0.046]**	[0.030]**	[0.049]**	[0.024]**
Application Denied	-0.0167	-0.0206	-0.0140	-0.0172
	[0.030]**	[0.006]***	[0.014]**	[0.032]**
Control Variables				
Official Supervisory Power	0.0131	0.0179	0.0147	0.0161
	[0.188]	[0.353]	[0.031]**	[0.534]
Supervisory Independence	0.0159	0.0164	0.0132	0.0151
	[0.023]**	[0.000]***	[0.045]**	[0.016]**
Bank Accounting Disclosure	0.0155	0.0184	0.0136	0.0177
	[0.035]**	[0.000]***	[0.043]**	[0.002]***
State Owned Banks	-0.0020	-0.0038	-0.0030	-0.0048
	[0.021]**	[0.000]***	[0.002]***	[0.040]**
Bank Size	0.0812	0.0734	0.0716	0.0620
	[0.000]***	[0.000]***	[0.000]***	[0.000]***
Bank Equity	0.0053	0.0066	0.0070	0.0076
	[0.012]**	[0.000]***	[0.035]**	[0.000]***
Inflation	-0.0014	-0.0019	-0.0010	-0.0026
	[0.013]**	[0.000]***	[0.025]**	[0.042]**
GDP per Capita	0.0072	0.0089	0.0055	0.0041
	[0.007]***	[0.000]***	[0.005]***	[0.093]*
GDP	0.0054	0.0086	0.0046	0.0074
	[0.032]**	[0.121]	[0.003]***	[0.017]**
Constant	0.2590	0.2369	0.2654	0.2054
	[0.022]**	[0.034]**	[0.000]***	[0.045]**
Pseudo R^2	0.201	0.210	0.137	0.284
Log likelihood	459.03	548.27	327.23	688.82
Observations	499	506	374	631

Note: Eq. (1) and (2) split the full sample of eq. (5) in Table 4 according to the variable of rule of law that is above the median level (with good rule of law eq. (1)) or below the median (with poor rule of law, eq. (2)), respectively. Eq. (3) and (4) split the full sample again into OECD countries plus Hong Kong and South Korea (high income countries, eq. (3)), and the remaining observations in the sample for eq. (4). The coefficients of the two variables related to information sharing, 'Information Sharing' and 'Depth of Credit Information', are both significantly bigger at the 1% level in countries with poor rule of law (eq. (2)) and low income (eq. (4)) than those in countries with good rule of law (eq. (1)) and high income (eq.(3)), respectively. The coefficient estimates are transformed to represent the marginal effects evaluated at the means of the independent variables from the interval regressions. P-values are in brackets. *, **, *** represent statistical significance at the 10%, 5% and 1% level respectively.