Profit efficiency of banks in Colombia with undesirable output: A directional distance function approach

This study investigates the sources of bank efficiency in Colombia over the period 2000-2011. To perform this research, we propose a score of bank efficiency using the directional distance function, which was estimated using data envelopment analysis. Additionally, we use an ordered probit panel regression to explore the effects of some market-related and bank-specific factors on efficiency. Our results show that the non-inclusion of non-performing loans (NPLs) leads to higher bank inefficiency indicators, which are significantly different from those obtained when NPLs are included. Further, we find that economic growth, capital risk, foreign and national banks, and account liquidity risk explain, in part, the efficiency of Colombian banks.

Keywords: Data Envelopment Analysis, Colombia, Directional Distance Function, Non-performing loans, Ordered Probit Panel Models.

JEL classification: D22, G21.

1. Introduction

The general conditions of the banking industry have changed worldwide during the past two decades due to deregulation and technological change.[1] Apart from the regulatory developments, there have been rapid and significant advances in information technologies, which have not only made possible the emergence of new financial products and services, production processes, and organizational forms, but also have led to an increase in the competition within the industry and to the expansion of the production possibilities of banks.[2] Due to the regulatory and technological changes as well as the importance of the banking sector, from both a microeconomic and macroeconomic perspective, the academic literature on different aspects of banking activity, especially on bank efficiency, is voluminous. The early empirical literature, which analyzed the efficiency and productivity of financial institutions by using either parametric or non-parametric frontier methods, is mainly dominated by studies on the United States and other industrialized countries (Berger & Humphrey, 1997; Amel *et al.*, 2002, Fiordelisi *et al.*, 2011). In recent years, however, great attention has been devoted to analyzing the efficiency and productivity of banking sectors in developing economies (e.g., Carvallo & Kasman, 2005; Staikouras *et al.*, 2008; Olson & Zoubi, 2011. Vu & Nahm, 2013) and studying the impact of the macroeconomic environment on banking efficiency (e.g., Drake *et al.*, 2006; Sufian, 2009), as well as to financial deregulation (e.g., Das & Ghosh, 2009; Pasiouras, 2009; Barth *et al.*, 2013, Chortareas *et al.*, 2009)

Other studies have explored the effects of bank-specific characteristics on performance by incorporating into the analysis, for example, bank strategy, ownership structure, corporate governance and risk-taking, liquidity levels, capital, and loan-loss provisioning, among other aspects.[3] Loans represent a major share of the total outputs provided by a bank, but as lending involves risk, there is always the possibility for a loan to become non-performing (Chang & Chiu, 2006). Thus, non-performing loans (NPLs) are the byproducts of producing loans and, thereby, are undesirable outputs. Hence, NPLs may have an impact not only on bank stability, but also on bank efficiency.

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[1] See Berger (2003) for an analysis of technological progress and its effects on the banking industry.
[2] See Frame and White (2002) for a review of the empirical literature on the adoption of innovations in banking.
[3] See Wilson *et al.* (2010) for a detailed review of the recent literature that has focused on the core themes of the performance, risk, and governance of financial institutions.

Despite the possible link between NPLs and bank efficiency, the empirical and methodological research in this area has been somewhat limited, compared to other fields (Pestana *et al.*, 2012). Berg *et al.* (1992) model the production technology of banks by directly incorporating the quality of assets; however, they do not use NPLs as an undesirable output. Park and Weber (2006) use the directional technology distance function to estimate the inefficiency and productivity change of Korean banks for the period 1992-2002. They treated NPLs as an undesirable byproduct arising from the production of loans and included them directly in the production process. Fukuyama and Weber (2008) used the directional distance function to estimate the inefficiency and the shadow price of NPLs of Japanese banks for the period 2002-2004. They concluded that researchers examining the efficiency of Japanese banks should control for NPLs as an undesirable byproduct of the loan production process. Pestana *et al.* (2012) followed the same approach to estimate the technical efficiency of Japanese banks for the period 2000-2007. They showed that incorporating NPLs into applied models might provide bank managers and policymakers an additional dimension in their decision processes.

More recently, Assaf *et al.* (2013) use a Bayesian stochastic frontier approach to analyze the productivity and efficiency of Turkish banks, focusing on accounting for NPLs. They proved that not accounting for NPLs in estimating the frontier model might seriously distort the efficiency and productivity results. Finally, Fujii *et al.* (2014) used the same methodological approach introduced by Pestana *et al.* (2012) to examine technical efficiency and productivity growth in the Indian banking sector over the period 2004-2011. They also found that NPLs are one of the main factors that contribute to bank inefficiency in India.

There has been some empirical research on bank performance in Colombia motivated by the structural financial reforms implemented during the first half of the 1990 to promote, among other things, competition and efficiency, via the liberalization of the financial system to foreign investment. In particular, the efficiency of the Colombian banking sector has been analyzed using parametric methods, among others, by Castro (2001), Badel Flores (2002), Estrada and Osorio (2004), Estrada (2005), and Fernandez and Estrada (2013). Non-parametric methods were used by Almanza-Ramírez (2009) and Sarmiento *et al.* (2013). All of the abovementioned studies implicitly assume that the banking production process does not generate byproducts; thus, they were not included when measuring efficiency. Based on this, the primary aim of this paper is to contribute to the empirical literature on bank efficiency by using the directional distance functions, introduced by Chambers *et al.* (1996), to determine the effects of the joint production of good and bad outputs on the efficiency of Colombia banks. In the second stage, we use a panel probit model regression in order to examine the influence of some environmental and bank-specific factors on efficiency in the banking system. The remainder of this paper is structured as follows. Section 2 provides a description of the method and its limitations. Section 3 describes the dataset and variables used. The results of the data envelopment analysis (DEA) models and ordered probit panel regression are presented in Section 4. Finally, the major conclusions are discussed in Section 5.

2. Methodological issues

DEA has been widely used to measure the efficiency of the financial sector. Contrary to parametric approaches, the non-parametric DEA method does not require any assumption to be made about the production process. Most of the empirical literature centered on evaluating banking efficiency through DEA does not consider that desirable and undesirable outputs are jointly produced and, thus, undesirable outputs are not taken into the account when evaluating performance.

Undesirable outputs have been incorporated into DEA by different methods. Scheel (2001) classifies these methods as indirect and direct approaches. In the indirect approach, the values of the undesirable outputs are transformed and, then, included as normal outputs to model the reference technology. The direct approach uses the original output data, assuming the validity of the null-jointness hypothesis, but modifies the assumption on the structure of the reference technology set, particularly, considering that good outputs are strongly disposable and bad outputs are weakly disposable.

Within the direct approach framework, we use the directional distance function to estimate banking efficiency in Colombia taking into account the production of undesirable outputs. Consider a production process that uses a set of inputs denoted by $\boldsymbol{x} = (x_1, \dots, x_n) \in \mathbb{R}_+^N$ to jointly produce a set of desirable outputs denoted by $y = \{x_1, \dots, x_n\} \in \mathbb{R}_+^M$ and set of undesirable outputs denoted by $b = \{b_1, \dots, b_j\} \in \mathbb{R}_+^J$, through a technology that can be described in a general way as follows.

$$T = \{(x, y, b): f(x) = (y, b)\} \quad (1)$$

The set T describes all input-output combinations that are technologically feasible. T is assumed compact and convex, and satisfies the assumptions of no free lunch and strong disposability of inputs and desirable outputs, and weak disposability of undesirable outputs. The directional distance function, which directionally measures the maximum attainable expansion of desirable outputs, as well as the contraction of undesirable outputs and inputs, is formally defined as follows:

$$\vec{D}\left(x, y; -g_x, g_y, -g_b\right) = \max\{\beta: \left(x - \beta g_x, y + \beta g_y, b - \beta g_b\right) \in T\}, \tag{2}$$

where $g = (-g_x, g_y, -g_b)$ is a non-zero vector that gives the direction in which the desirable outputs, undesirable outputs, and inputs are scaled. Moreover, it can be demonstrated that $\vec{D}_T\left(x, y; -g_x, g_y, -g_b\right) \geq 0$ if (x, y, b) is an interior point of T, and $\vec{D}_T\left(x, y; g_x, g_y\right) = 0$ if and only if (x, y) is on the boundary of T; therefore, Equation (2) measures technical efficiency.[4] We assume that there exists a set of banks $\{1, \dots, K\}$ in the dataset. Each bank k uses the input vector $x_k^t = \{x_{1k}^t, \dots, x_{nk}^t\}$ to jointly produce the desirable output vector $y_k^t = \{y_{1k}^t, \dots, y_{mk}^t\}$ and undesirable output vector $b_k = \{y_{1k}^t, \dots, y_{jk}^t\}$. Good and bad outputs are jointly produced (null-jointness hypothesis), that is, to produce a positive amount of desirable outputs, some bad outputs will also be produced. Formally, null-jointness is modeled as follows.

$$(x, y, b) \in T \text{ and } b = 0 \Longrightarrow y = 0 \tag{3}$$

Following Färe *et al.* (1988), the observed inputs as well as the desirable and undesirable outputs of all banks are used to construct a piecewise reference technology, T, as follows:

$$T = [(x, y, b): \sum_{k=1}^{K} z_k x_{nk}^t \leq x_n^t, \qquad n = 1, \dots, N,$$

$$\sum_{k=1}^{K} z_k y_{mk}^t \geq y_m^t, \qquad m = 1, \dots, M,$$

$$\sum_{k=1}^{K} z_k b_{jk}^t = b_j^t, \qquad l = 1, \dots, L,$$

[4] See Luenberger (1992) and Chambers *et al.* (1996) for detailed discussions on the additional properties of the directional distance functions.

$$\sum_{k=1}^{K} z_k = 1,\ z_k \geq 0, \qquad k = 1, \ldots, K, \tag{4}$$

where the intensity variables, z_k, serve to form convex combinations of all banks' observed inputs and outputs. The sum of the intensity variables is restricted to be one to model variable returns to scale, which allows for the consideration that some banks may have positive, negative, or zero profits.[5] The inequalities for inputs and good outputs make them freely disposable. Finally, the weak disposability and null-jointness hypothesis are imposed through the equality of the undesirable output constraints. Taking the directions g_x, g_y, and g_b to be the observed input, desirable output, and undesirable output vector of each bank, that is, $g_x = x_{nk}^t$, $g_y = y_{mk}^t$, and $g_b = b_{jk}^t$, the directional distance function can be calculated non-parametrically from equation (4) by solving:

$$\vec{D}(x, y, b; -g_x, g_y, -g_b) = \max \beta \quad s.t.$$

$$(1-\beta)x_{nk}^t \geq \sum_{k=1}^{K} z_k x_{nk}^t \qquad n = 1, \ldots, N,$$

$$(1+\beta)y_{mk}^t \leq \sum_{k=1}^{K} z_k y_{mk}^t \qquad m = 1, \ldots, M,$$

$$(1-\beta)b_{jk}^t = \sum_{k=1}^{K} z_k b_{jk}^t \qquad j = 1, \ldots, J,$$

$$x_{n+1,k} \geq \sum_{k=1}^{K} z_k x_{n+1,k},$$

$$\sum_{k=1}^{K} z_k = 1 \qquad k = 1, \ldots K, z_k > 0. \tag{5}$$

Following Färe *et al.* (1994), an additional input constraint has been added in (5), for the $n+1$ input, in order to incorporate the equity as a quasi-fixed input. The solution to (5) will yield technical efficiency measures for each firm in the sample. A firm may be technically efficient, but operating at a sub-optimal scale of production, so it can improve its productivity by exploiting economies of scale. Following Fukuyama (2003), we define the scale efficiency indicator as:

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[5] See Chapter 2 in Färe *et al.* (1994) for a detailed discussion on the construction of reference technologies under different assumptions regarding returns to scale.

$$\vec{S}(x, y, b; -g_x, g_y, -g_b) = \vec{D}^{NI}(\cdot) - \vec{D}^{ND}(\cdot), \tag{6}$$

Where NI and ND denote non-increasing and non-decreasing returns to scale, respectively. Note that the Scale Efficiency Indicator (6) requires the measurement of the technical efficiency regarding technologies showing NI and ND returns to scale. To measure the technical efficiency from a piecewise technology under NI, we let the sum of the intensity variables, z_k, in (5) be less or equal to one.

Similarly, letting the sum of the intensity variables be greater or equal to one allows us to measure technical efficiency under ND return to scale. $EF^{\vec{S}}(\cdot) = 0$ implies that the bank is scale-efficient. Whether $EF^{\vec{S}}(\cdot) < 0$ or $EF^{\vec{S}}(\cdot) > 0$, the bank shows decreasing or increasing returns to scale, respectively. To determine the source of scale inefficiencies, we rely on the following criteria (Fukuyama, 2003).

i. The technology exhibits decreasing returns to scale if
$$\vec{D}^{NI}(x, y, b; -g_x, g_y, -g_b) < \vec{D}^{ND}(x, y, b; -g_x, g_y, -g_b).$$
ii. The technology exhibits increasing returns to scale if
$$\vec{D}^{NI}(x, y, b; -g_x, g_y, -g_b) > \vec{D}^{ND}(x, y, b; -g_x, g_y, -g_b).$$
iii. The technology exhibits constant returns to scale if
$$\vec{D}^{NI}(x, y, b; -g_x, g_y, -g_b) = \vec{D}^{ND}(x, y, b; -g_x, g_y, -g_b).$$

Once the profit technical efficiency measures are estimated, ordered probit panel regression analysis is used to identify which market-related and bank-specific factors influenced the observed efficiency levels. The model is:

$$PTE* = \beta_0 + \sum_k^K \beta_k X_k + v_k, \tag{7}$$

such that:

$$PTE = \begin{cases} 1 & if\ PTE* \leq 0 \\ 2 & if\ 0 < PTE* \leq \mu_1 \\ 3 & if\ \mu_2 \leq PTE* \end{cases}.$$

Here, $PTE*$ is the exact, but unobserved profit technical efficiency scores; X_k is a vector containing the bank-specific and market-related variables; and v_k is an error term. When PTE is equal to three, the bank is totally efficient. In the case in which PTE is equal to two, the bank has a medium efficiency (if the value of efficiency is between zero and the median efficiency plus half of a standard deviation). Finally, if PTE is equal to one, the bank experiences an inefficiency (upper to median efficiency plus half a standard deviation).

3. Dataset and variable definition

The definition of the input and output factors is a condition absolutely necessary for the implementation of productivity or efficiency analyses. Due to the complexity of banking activities, there is no agreement among researchers on the inputs and outputs of a bank. Nevertheless, there are different approaches toward bank behavior (e.g., the intermediation, production, user cost, and value-added approaches), which can support the input and output specification.[6]

In this article, the intermediation approach of banking is used for the specification of inputs and outputs. According to this approach, banks are considered intermediators between agents in surplus and agents in deficit. That is, it is assumed that banks mainly transform and transfer financial resources from the former to the latter. This approach is particularly appropriate where the main activities of the bank consist of turning deposits and funds purchased from other financial intermediaries into loans and financial investments (Favero & Lapi, 1995).

The interest income (y_1) and non-interest income (y_2) are defined as desirable outputs and the NPLs, (b), as undesirable output. The interest expenses (x_1) and non-interest expenses (x_2) are defined as inputs. This input and output set is consistent with the intermediation approach to modeling bank behavior and is appropriate to cover the entire range of resources used and outputs created, while providing acceptable discriminatory power (Avkiran & Thoraneentiyan, 2010). Equity capital (x_3) is included as a quasi-fixed input when estimating the efficiency to account for risk preferences (Altunbas *et al*, 2007). Ignoring this variable could lead to mismeasurement of the efficiency of financial intermediaries that may be more risk-averse, even though they are behaving optimally. Furthermore, financial capital provides an

[6] For a brief discussion of the main characteristics of these theoretical approaches, see Favero and Lapi (1995), Avkiran (2006), and Burger (2008).

alternative funding source to banking assets; therefore, banks that have different equity-to-deposits ratios, have different cost and profit structures (Berger & Mester, 1997).

Table 1 provides some descriptive statistics of the inputs-outputs used in this study for the overall sample and for domestic and foreign banks over the period 2000-2011. The high variability of the variables, with respect to their mean values within each class of financial intermediaries, suggests that there are important differences between them. In fact, the results of the Kruskal-Wallis test indicate that there are statistically significant differences between the banks belonging to the same group with regard to their input and output levels.

Table 1. Descriptive statistics of variables Banks

	Variables	**Mean**	**CV**	**Kurtosis**	**skewness**
Foreign	Interest income (y_1)	243.7	1.17	13.00	2.79
	Non-interest income (y_2)	375.2	1.53	33.21	4.83
	NPLs (b)	63.7	1.50	22.47	3.75
	Interest expenses (x_1)	117.3	1.01	10.44	2.47
	Non-interest expenses (x_2)	270.2	1.73	29.99	4.55
	Equity(x_3)	328.9	1.68	44.90	5.87
Domestic	Interest income (y_1)	401.6	1.02	6.08	1.84
	Non-interest income (y_2)	477.3	1.69	18.17	3.64
	NPLs (b)	158.7	1.30	8.26	2.34
	Interest expenses (x_1)	170.4	0.97	6.64	1.88
	Non-interest expenses (x_2)	260.8	2.40	24.93	4.39
	Equity(x_3)	639.9	1.31	9.94	2.57
Total	Interest income (y_1)	336.6	1.10	7.84	2.15
	Non-interest income (y_2)	435.3	1.65	22.53	4.05
	NPLs (b)	119.6	1.47	11.95	2.88
	Interest expenses (x_1)	148.5	1.00	8.00	2.12
	Non-interest expenses (x_2)	264.7	2.13	27.64	4.54
	Equity(x_3)	511.9	1.46	15.29	3.28

Source: Own computations. Total sample 17 Banks: foreign banks (7), domestic Banks (10). Variables in millions of US Dollars.

On the other hand, the Mann-Whitney test, which was used to compare the two groups, shows that domestic and foreign banks have no statistically significant differences only in their non-interest income levels.[7]

[7] Non-parametric tests were used due to the Shapiro-Wilk test for normality rejecting the hypothesis of the normality of the variables.

To select the relevant market-related and key bank-specific characteristics to be included in the econometric model, we turn to the empirical literature, due to the lack of theoretical explanations concerning the factors that may affect efficiency (see Dietsch & Lozano, 2000; Carvallo & Kasman, 2005; Arrif & Can, 2008). The descriptions of the selected variables are summarized in Table 2.

Table 2. Description of the relevant market-related and key bank-specific variables

Variables	Symbol	Description
Market-related		
Economic cycle (%)	EG	Growth rate of GDP
Bank-specifics		
Liquidity risk (%)	GLTD	Loans/Deposits
Capital risk (%)	ETA	Equity/total assets
Ownership structure (%)	OWN	1= foreign banks, 0=domestic

Source: Own selection.

The growth rate of GDP (EG) is used to take into the account the effect of the economic cycle on efficiency. The variables of gross loans to deposits (GLTD) and equity to total assets (ETA) are used to account for liquidity risk and capital risk, respectively. Ownership structure (OWN) is a dummy variable used to include the differences in efficiency among national and foreign banks. Descriptive statistics for the environmental and bank-specific variables are provided in Table 3.

Table 3. Statistics of the relevant market-related and key bank-specific variables

Market-related	mean	CV	Skewness	Kurtosis
EG %	4.3	0.42	-0.10	1.97
Bank specifics (Total)				
GLTD %	84.4	0.11	0.46	2.25
ETA %	11.4	0.10	0.48	1.89
Bank-specifics (Domestic)				
GLTD %	84.3	0.10	0.46	2.24
ETA %	11.3	0.09	0.48	1.89
Bank-specifics (Foreign)				
GLTD %	84.3	0.10	0.46	2.24

ETA %	11.3	0.09	0.48	1.89

Source: Own computations.

4. Empirical results

The Colombian banking industry consisted of 17 banks from 2000-2007 and grew to 18 from 2005-2007, to 20 from 2008-2010, and to 23 in 2011. We selected the banks that were operating over the period 2000-2011 and, from the balance sheets and income statements compiled by the Colombian Supervision Authority—Superintendencia Financiera—we built a balanced panel dataset of 204 observations, which included a total of 17 banks: 10 domestic and seven foreign. Domestic banks are larger and seem to be less specialized in commercial loans than are foreign banks; hence, they have a greater number of offices throughout the country.[8]

The DEA methodology was applied to the dataset to measure the profit-oriented technical efficiency of Colombian banks. Initially, we estimated two models using directional vectors $g_x = x_{nk}^t$, $g_y = y_{mk}^t$, and $g_b = b_{jk}^t$, that is, the observed inputs and outputs for each bank. In Model 1, however, the byproducts, b_{jk}^t, are not considered when measuring efficiency.

The number of banks that defined the frontier for each year is reported in Table 4. The results show that when the byproducts are included in the measurement of efficiency, the average number of banks that built the frontier increased from 11 (67% of the sample) in Model 1 to 14 (82% of the sample) in Model 2. The difference in the number of frontier banks between the two models could be partially explained by the treatment of undesirable outputs: banks that appear to be inefficient are efficient when the undesirable outputs are considered.

[8] The mean value of the ratios of commercial loans to gross loans and consumer loans to gross loans for the domestic banks are 0.56763 and 0.29801, respectively, while the average of the same ratios for the foreign banks are 0.6720 and 0.2982, respectively. For the period 2000-2011, the domestic and foreign banks have average assets of \$5.5 and \$2.7 billion USD, respectively. The Mann-Whitney test rejects at 95% significance the equality of the average assets ($z = 4.181, p > |z| = 0.0000$) and commercial loans/total loans ratios ($z = -2.636, p > |z| = 0.0084$) between both groups. The observed positive and negative z-values show that domestic banks have a higher level of assets and lower commercial-to-total-loans ratios than do foreign banks.

Table 4: Technically efficient banks

	Model 1 $\vec{D}_k^t(x_{nk}^t, y_{mk}^t; -g_x, g_y)$			Model 2 $\vec{D}_k^t(x_{nk}^t, y_{mk}^t, b_{jk}^t; -g_x, g_y, -g_b)$		
Year	Total	Domestic	Foreign	Total	Domestic	Foreign
2000	11	8	4	15	9	6
2001	14	9	5	15	9	6
2002	13	8	5	15	8	7
2003	9	7	2	14	9	5
2004	9	7	2	14	8	6
2005	10	7	3	14	9	5
2006	11	6	5	12	6	6
2007	12	10	2	11	5	6
2008	12	7	5	14	8	6
2009	11	7	4	15	9	6
2010	12	6	6	14	7	7
2011	13	8	5	14	8	6
mean	11	7	4	14	8	6
%	67	44	24	82	47	35

Total sample: 17 banks. $g_x = x_{nk}^t$, $g_y = y_{mk}^t$ and $g_b = b_{jk}^t$
Frontier banks have $\vec{D}(\cdot) = 0$

Source: Own computations.

Table 5 presents the estimated profit-oriented technical inefficiency of the Colombian banks. The average inefficiency was 3.7% in Model 1 and 1.1% in Model 2. The Wilcoxon signed-rank test reveals that the differences between the average efficiency scores in both models are significant, especially that the average inefficiency in Model 1 is higher than that in Model 2.[9] This result seems to confirm that not taking the NPLs into account could overestimate the inefficiency measurements.

On the other hand, given that foreign banks operate in several countries, especially in developed countries where the financial markets are more developed and, thus, more competitive, one would expect to observe the better performance of foreign banks than of their domestic counterparts.

[9] The Wilcoxon signed-rank test rejects at 95% significance the null hypothesis of mean equality$(z = 8.134, p > |z| = 0.0000)$; the positive z-value indicates that the mean of the first model is higher than that of the second model.

However, the comparison of the two scenarios contradicts this hypothesis.[10] This result could be evidence of the adaptive behavior of the foreign banks to the level of competition in the Colombian banking sector.

The directional distance function measures the maximum expansion in desirable outputs and simultaneous contraction in inputs and undesirable outputs that is technologically feasible. In Model 1, for example, we estimated a sample average inefficiency of 0.037 (3.7%). Based on the averages reported in Table 1, it could be said that, in millions of USD, the banks, on average, could expand interest income by $\$336.6 \times 0.037 = \$12.5$, expand non-interest income by $\$435.3 \times 0.037 = \$16.1$, and contract NPLs by $\$119.6 \times 0.037 = \$4.4$, while generating $0.037 \times 148.5 = \$5.5$ less interest expenses and $0.037 \times 264.7 = \$9.8$ less non-interest expenses.

Concerning the scale efficiency, the results presented in Table 6 show that, on average, 60% of banks were characterized as scale-inefficient, 63% of which were domestic. Moreover, our analysis reveals that, basically, the observed scale inefficiency can be attributed to the decreasing returns to scale, as 80% of scale-inefficient banks are operating their production technology in this region; consequently, they can improve their productivity by reducing their scale of operations.

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[10] The results of the Mann-Whitney test are $z = -1.566, p > |z| = 0.117$ for Model 1 and $z = 1.037, p > |z| = 0.2996$ for Model 2.

Table 5: Technical inefficiency of Colombian's banks

	Model 1 $\vec{D}_k^t(x_{nk}^t, y_{mk}^t; -g_x, g_y)$			Model 2 $\vec{D}_k^t(x_{nk}^t, y_{mk}^t, b_{jk}^t; -g_x, g_y, -g_b)$		
	Sample	Domestic	Foreign	Sample	Domestic	Foreign
2000	0.037	0.039	0.034	0.002	0.000	0.005
2001	0.033	0.039	0.025	0.008	0.005	0.011
2002	0.011	0.015	0.005	0.006	0.010	0.000
2003	0.049	0.028	0.078	0.015	0.010	0.022
2004	0.041	0.033	0.052	0.012	0.016	0.006
2005	0.050	0.031	0.077	0.009	0.011	0.007
2006	0.045	0.046	0.042	0.024	0.031	0.015
2007	0.062	0.051	0.078	0.021	0.026	0.013
2008	0.042	0.027	0.065	0.007	0.004	0.012
2009	0.024	0.028	0.017	0.005	0.002	0.009
2010	0.034	0.042	0.023	0.010	0.017	0.000
2011	0.020	0.020	0.019	0.013	0.015	0.009
Mean	0.037	0.033	0.043	0.011	0.012	0.009
S.d	0.072	0.072	0.073	0.029	0.031	0.027
Max	0.062	0.051	0.078	0.024	0.031	0.022
Min	0.011	0.015	0.005	0.005	0.002	0.000

$g_x = x_{nk}^t$, $g_y = y_{mk}^t$ and $g_b = b_{jk}^t$

Source: Own computations.

The sum of the directional distance functions is a measure of industry performance if the efficiency for each firm is calculated for a common directional vector (Färe & Grosskopf, 2004). We used two different common vectors to estimate the efficiency of the Colombian banking sector: $g_x = \bar{x}$, $g_y = \bar{y}$, and $g_b = \bar{b}$, and $g_x = \bar{x}^t$, $g_y = \bar{y}^t$, and $g_b = \bar{b}^t$. That is, the mean input-output values, as reported in Table 7 (Model 3), and the yearly averages of the output-inputs of all banks (Model 4). The results are reported in Table 7.

For the period 2000-2011, we estimated an average industry inefficiency of 8.6% and 14.9% with Models 3 and 4, respectively. Considering the results of Model 4, this means that during this period, the technical inefficiency of the banking industry could be eliminated by increasing the interest and non-interest incomes by \$336.6 × 0.149 = \$50 and \$435.3 × 0.149 = \$64.8, respectively, and by decreasing the NPLs by \$119.6 × 0.149 = \$17.8, while generating 148.5 × 0.149 = \$22.1 less interest expenses and 264.7×0.149 = \$39.4 less non-interest expenses. The observed higher inefficiency levels in 2009 (48.3% in Model 4) could be explained by the effects of the international financial crisis on the Colombian economy. The financial crisis caused a decrease in the general economic activity and, therefore, a dramatic decline in the growth rate of loans granted as well as further deterioration of the portfolio. In effect, the growth rate of the GDP fell from 6.5% in 2007 to 1.7% in 2009. Furthermore, according to the information from the Colombian Supervision Authority, the growth rate of the portfolio and leasing operations declined from 25% in 2007 to 17% in 2008 and 1.8% in 2009, while the quality of the portfolio index increased by 1.6%.

Table 6: Source of Scale Inefficiency of Colombian Banks

		Domestic(10)			Foreign (7)						
Year	SE	DRS	IRS	%	DRS	IRS	%	Inefficient	%	Efficient	%
2000	-0,009	3	3	67	2	1	33	9	53	8	47
2001	-0,009	4	2	60	2	2	40	10	59	7	41
2002	-0,010	5	2	78	1	1	22	9	53	8	47
2003	0,002	4	2	55	2	3	45	11	65	6	35
2004	-0,021	6	2	57	4	2	43	14	82	3	18
2005	-0,009	4	3	58	2	3	42	12	71	5	29
2006	-0,058	6	1	58	5	0	42	12	71	5	29
2007	-0,033	6	2	67	3	1	33	12	71	5	29
2008	-0,020	4	3	64	3	1	36	11	65	6	35
2009	-0,035	6	0	60	2	2	40	10	59	11	65
2010	0,000	4	2	60	1	3	40	10	59	7	41
2011	-0,025	3	0	50	3	0	50	6	35	11	65
Mean	-0,019	5	2	63	3	2	37	10	60	7	40

Decreasing Returns to Scale (DRS), Increasing Returns to Scale (IRS).

Source: Own computations.

4.1 Efficiency analysis

In order to discuss the effect on bank efficiency, we model the probability of the efficiency as an ordered probit panel model.

Consider the efficiency as a discrete variable where the low value is total efficiency, middle value is medium inefficiency, and high value is below the medium inefficiency of the banks.

We used the efficiency scores, calculated through Model 1, as the dependent variable and the interaction between economic growth and a dummy for year 2008 as covariables to capture the global crisis effects (GDP*D2008). Considering account liquidity risk (GLTD) and the interaction between capital risk (ETA) and ownership structure (OWN) (ETA*OWN), including differences in efficiency among the capital risk of national and foreign banks, we found that the probability of a low value of efficiency is 17%, of medium efficiency is 16.76%, and of total efficiency is 66.14%. We calculate the marginal effects in Table 7.

Table 7. Marginal Effects of the Probit Panel Efficiency Model

	Marginal Effects	Std. Err.	t-Value
Economic Cycle			
Low efficiency	0.0183191	0.008528	2.15
Medium effiency	0.0081729	0.0043587	1.88
Total Efficiency	-0.026492	0.0109637	-2.42
Financial Deepening			
Low efficiency	-0.745687	0.3899252	-1.91
Medium effiency	-0.3326802	0.1960776	-1.70
Total Efficiency	1.078367	0.517069	2.09
Capital Risk			
Low efficiency	1.687992	0.8531858	1.98
Medium effiency	0.7530795	0.2840251	2.65
Total Efficiency	-2.441072	0.9585999	-2.55

Source: Own computations using Delta Method.

Similar to Levine (1997), our results show that there is a positive relationship between efficiency and economic growth, that foreign banks exhibit more efficient results using capital risk, and that account liquidity increases bank efficiency. All variables are statistically significant. We further explore this relationship using the marginal effects (see Table 7).

The economic growth had a positive and significant effect on efficiency; that is, it increased the high efficiency and reduced the low efficiency. Further, we observed differences in efficiency among national and foreign banks due to capital risk; in foreign banks, capital risk decreased efficiency, when compared to national banks. Finally, account liquidity risk increased bank inefficiency.

5. Concluding remarks

This paper presents a two-stage approach to Colombian bank efficiency over the period 2000-2011. In the first stage, we obtained measures of bank inefficiency from the directional distance function, which was estimated using DEA. In the second stage, we used Tobit regression to explore the effects of some environmental and bank-specific factors on efficiency. The directional distance function allowed us to aggregate individual bank efficiency indicators to the industry level and control for NPLs, which are treated as a byproduct of the banks' production processes. We show that not including the NPLs leads to higher bank inefficiency indicators, which are significantly different from those obtained when including NPLs. Thus, we concluded, like Fukuyama and Weber (2008), that to analyze the efficiency of Colombian banks, NPLs should be included as an undesirable output. Additionally, we found strong empirical evidence that foreign banks do not perform better than do their domestic counterparts. This could be evidence of the adaptive behavior to the low concurrence within the Colombian banking sector.

On the industry level, we estimated an inefficiency of 14.9%, that is, a profit-oriented technical efficiency of 85.1%, while Estrada and Osorio (2004) reported an average alternative profit efficiency of 88%. Thus, we can conclude that there is a slight profit efficiency decrease from the period 1989-2003 to 2000-2011.

Finally, we observed differences in efficiency among national and foreign banks due to capital risk; in foreign banks, capital risk decreased efficiency, when compared to national banks. Finally, account liquidity risk increased bank inefficiency.

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