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Efficiency Determinants and Dynamic Efficiency Changes in Latin American Banking Industries

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Abstract

This paper investigates the determinants of efficiency and dynamic efficiency changes across Latin American banking industries during recent periods of financial liberalization. Allocative, technical, pure technical, and scale efficiency measures are calculated and analyzed for seven Latin American countries. Consistent with extant literature, profit inefficiency is higher than cost inefficiency across our sample, suggesting that most of the profit inefficiency comes from the revenue side. The decomposition of revenue efficiency into revenue allocative efficiency and technical efficiency suggests that the source of inefficiency is regulatory (allocative) rather than managerial (technical). Moreover, consistent with what practitioners would expect, efficient banks have lower overhead costs relative to total income, use resources better, have higher quality portfolios, and have higher earnings (e.g., higher return on assets – ROA and return on equity – ROE) than inefficient ones. Furthermore, financial liberalization has brought productivity increases throughout Latin America; but this increase in productivity is a consequence of technological progress rather than enhanced technical efficiency.

Keywords: Latin American banks, cost, profit, revenue efficiency, productivity index

JEL Classification codes: D2, G2, G21, G28

Financial liberalization took place in many Latin American countries in the late 1980s. Specifically, for the banking sector, financial liberalization eliminated government interest rate controls and bank obligations to provide subsidized loans, and it allowed central banks more autonomy. These reforms in the Latin American banking industries were intended to improve banking efficiency.[1] Unfortunately, financial liberalization in the region was accompanied by neither an effective regulatory and normative framework nor effective monitoring of Latin American banking systems.

In many Latin American countries, a more competitive banking environment followed financial liberalization; but along with this increase in competition came a decrease in demand for credit due to economic instability. As a consequence, banks looked for new sources of profitability. For example, many large Latin

American banks purchased unrelated companies that required a number of banking managers to be transferred to business areas with which they were unfamiliar. Others acquired very risky, high-expected-yield, long-term investments such as junk bonds.

Taking on these risky investments, coupled with increasing economic disturbances, led to insolvency for some Latin American banks and subsequent banking crises in four Latin American countries between 1993 and 1995 (Venezuela, Mexico, Argentina, and Brazil). These crises were the consequence of external and internal economic factors, financial difficulties, lack of mandatory capitalization, and bad managerial practices. Similar events led to banking crises in Colombia and Ecuador in the late 1990s.

One exception in the region is Chile, which did not have a banking crisis during the 1990s. This country implemented structural reforms in the 1980s and its banking industry operated in a relatively strong macro-economic environment. These conditions, along with a fairly strong regulatory system, allowed the banking system to develop without financial distress.

Latin American governments were forced to implement a series of additional reforms to escape the banking crises and to foster stable growth of the banking system. These reforms resulted in the opening of markets to foreign investment in the banking system, the creation of universal banks, and the closure or privatization of public sector banks. In general, governments passed stricter laws and regulations that required banks to adhere to the standards of the Basel Accords.

The reforms brought about consolidation of banking systems throughout Latin America and the consequent reduction in the number of banks through mergers and acquisitions. This led bankers, as well as the Latin American press, to claim that the new environment would lead to improvements in banking efficiency. Nevertheless, Berger and Humphrey (1997) noted mixed results in the literature, and there is no conclusive evidence that financial deregulation has improved efficiency in banking systems.

A question related to the gain or loss in efficiency is whether or not financial structure and macroeconomic health affect efficiency. For instance, Bossone and Lee (2004) argued that a well-developed financial system should support banking activities, making the banking industry more efficient. Additionally, the general health of a country's economy may affect banking efficiency. For example, high inflation reduces the amount of financing available to the private sector (Boyd, Levine, & Smith, 2001), and consequently banks have to reallocate their resources, affecting their economic efficiency.

This paper comprises a comprehensive examination of measures of cost, revenue, profit, cost allocative, technical, pure technical, and scale efficiency and their determinants in seven Latin American countries (Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Venezuela) during the period 1997 to 2007, a period of financial liberalization with a more stringent regulatory framework after banking crises in many of these countries. It is inherently interesting to investigate the evolution of banking efficiency after financial liberalization and after the crisis to assess whether the new environment had led to an improvement in banking efficiency.

We also study the determinants of banking efficiency in Latin America via bank-specific, financial structure, and macroeconomic variables. In a similar recent study on the determinants of Latin American banks' cost efficiency, Carvallo and Kasman (2005), studied cost efficiency determinants during the time period 1995-2001. However, our study differs from theirs in many ways. We estimate technical and economic efficiency (cost, revenue, and profit efficiency) using a nonparametric approach, whereas Carvallo and Kasman (2005) only estimated cost efficiency using a parametric approach. Moreover, our sample spans a broader and more recent time period (1997-2007) for 512 banks, whereas their study spans the period 1995-2001. More importantly, we use a more comprehensive set of explanatory variables, including bank structure, financial structure, and macroeconomic environment, to study the determinants of Latin American banking systems. Nevertheless, our study examines whether their conclusions hold using a nonparametric approach.

Some studies have used parametric and nonparametric techniques to study banking efficiency in Latin American countries. Using data envelopment analysis (DEA), Staub, Da Silva e Souza, and Tabak (2010) studied cost, technical, and allocative efficiency for Brazilian banks during the period 2000-2007 and found that Brazilian banks had low levels of economic (cost) efficiency compared to banks in Europe and in the United States of America. Additionally, the economic inefficiency in Brazilian banks could be attributed mainly to technical inefficiency rather than allocative inefficiency during 2000-2002, and state-owned banks were more efficient than foreign banks, private domestic banks, and private banks with foreign participation. Fuentes and Vergara (2007) estimated profit and cost efficiency for Chilean banks during the period 1990-2004 using stochastic frontier approach (SFA). They found that banks that were established as listed companies had higher efficiency measures than those that were established as closed companies. Further, they found that banks with a high property concentration had a higher level of efficiency. Taylor, Thompson, Thrall, and Dharmapala (1997) used DEA to estimate efficiency for Mexican banks and classified them as efficient or inefficient banks. Guerrero and Negrin (2005), using SFA on a sample of Mexican banks, found that bank efficiency decreased during the period 1997-2001, but efficiency scales have been increasing in Mexico since 2001. More recently, Charles, Kumar, Zegarra, and Avolio (2011) investigated the efficiency of Peruvian banks during the period 2000-2009 using DEA. They found an increasing trend in technical efficiency after the banking system reforms, and that multinational banks performed better than domestic banks. Portela and Thanassoulis (2006) used a nonoriented DEA decomposition measure to study the efficiency change, technology change, and residual measures in a sample of Portuguese banks. The authors argued that use of distance functions as a means to calculate total factor productivity (TFP) change may introduce bias, and they introduced a new procedure to calculate TFP with observed values only. Camanho and Dyson (1999) also used DEA to examine the performance of a sample of Portuguese bank branches. Their analysis focused on the relationship between bank size and performance.

Some studies have focused on a set of Latin American countries rather than a single country. Rivas, Ozuna, and Policastro (2006) studied whether the use of derivatives affected bank efficiency in Brazil, Chile, and Mexico and found that efficiency was positively associated with larger banks. Moreover, they found that regulatory and institutional constraints were negatively related to efficiency. Forster and Shaffer (2005) investigated the association between efficiency, size, and market share. They found a robust association between absolute size and efficiency but not between relative size and efficiency. Chortareas, Garza-Garcia, and Girardone (2011) investigated "whether banks earn supernormal profits because they are exercising market power or as a result of achieving higher efficiency levels" (p. 321). They found evidence supporting the latter: More efficient banks in Latin American are also highly profitable. Moreover, capital ratios and bank size are among the most important factors explaining profitability. Finally, Carvallo, and Kasman (2005) used a stochastic frontier model to estimate cost inefficiencies and scale and scope economies for 481 banks in 16 Latin American countries. They found that very small and very large banks tended to be more inefficient and underperforming (inefficient) banks tended to be undercapitalized, to present poor profit performance, to be more dependent on noninterest income, to be more risky, to have a less stable deposit base, and to intermediate less.

This paper investigates the major sources of economic inefficiency; the causal relationships between economic efficiency and bank-specific performance, financial structure, and economic conditions; and changes in efficiency and productivity after deregulation in a more stringent regulatory framework in Latin America. We first analyze absolute efficiency and trace the sources of inefficiency in each country. We then investigate the determinants of the different efficiency measures by performing censored Tobit regressions with year and country fixed effects of estimated efficiency on bank-level performance ratios, country-level financial and banking infrastructure measures, and country-level macroeconomic performance. In addition, we examine the relative changes in efficiency and the TFP index over the period 1997 to 2007. DEA is used to compute absolute efficiency, as well as Malmquist indices to characterize productivity changes in each country.

Consistent with extant literature, we find that profit inefficiency is higher than cost inefficiency across our sample, suggesting that most of the profit inefficiency comes from the revenue side. The decomposition of revenue efficiency into revenue allocative efficiency and technical efficiency suggests that the source of inefficiency is regulatory (allocative) rather than managerial (technical). Moreover, consistent with what practitioners would expect, efficient banks have lower overhead costs relative to total income, use resources better, have higher quality portfolios, and have higher earnings (e.g., higher ROA and ROE) than inefficient ones. Furthermore, financial liberalization has brought productivity increases throughout Latin America, but this increase in productivity is a consequence of technological progress rather than enhanced technical efficiency.

The remainder of this paper proceeds as follows. In the next section, we show how efficiency is estimated, and we also discuss the estimates of sample statistics for inputs, outputs, and prices. In the third section, we analyze and trace the sources of inefficiency in each country. Next, we explain the determinants of Latin American banking efficiency, and then, we examine productivity changes throughout Latin American banking systems. The final section concludes the paper.

Estimation of Efficiency

A firm's productivity is the ratio of outputs to inputs, which depends upon production process technology and differences in the environments in which production occurs, among others variables. The firm's efficiency is a comparison between observed and optimal values of outputs and inputs. The set of the optimal outputs, given the inputs (or the optimal inputs, given the outputs) is the efficient frontier. Farrell (1957) defined a simple measure of firm efficiency that could account for multiple inputs. He proposed that efficiency of any firm consists of two components: (a) *technical efficiency*, the ability of the firm to maximize outputs from the given set of inputs; and (b) *allocative efficiency*, the ability of the firm to use these inputs in optimal proportion given their respective prices. Combining these two components provides a measure of economic efficiency, which is also known as productive or overall efficiency.

An alternative measure of economic efficiency is *cost efficiency*, which measures how far a bank's costs deviate from the best practice bank's costs, producing at the same level of output and under the same environmental conditions. Cost *efficiency* can be decomposed into *technical efficiency* and *allocative efficiency*. The level of *technical efficiency* is usually related to managerial decision making, while *allocative efficiency* is usually related to regulatory environment or macroeconomic conditions (Lovell, 1993).

Technical efficiency can be further decomposed into two parts: *scale efficiency* and *pure technical efficiency*. *Pure technical efficiency* refers to the firm's ability to avoid waste by producing as much output as input usage allows or by using as little input as output production allows. Scale efficiency refers to the firm's ability to work at its optimal scale.

Other measures of economic efficiency are *revenue efficiency* and *profit efficiency*. *Revenue efficiency* measures the ratio between current revenues and optimal revenues, given prices and outputs, while *profit efficiency* measures the ratio of current profits to optimal profits, given inputs, outputs, and their respective prices.

In summary, we calculate cost, revenue, and profit efficiency and further decompose cost efficiency into technical and allocative efficiency. We then decompose technical efficiency into pure technical efficiency and scale efficiency in order to understand more fully the underlying determinants of efficiency in Latin American banking industries.

In order to calculate these efficiency measures, a production function of a benchmark efficient firm must be estimated from sample data. There are two approaches to approximate the efficient production function: the parametric approach and the nonparametric approach. These approaches use different techniques to envelop the observed data and make different accommodations for random noise and for the flexibility in the structure of the production technology (Lovell, 1993).

The parametric (or econometric) approach specifies a production function and recognizes that deviation away from this given technology is given by two components, one representing statistical noise and the other inefficiency. The random term is due to events outside the control of the firm, (e.g., uncontrollable factors directly related to the production function) or econometric error such as misspecification of the production function or measurement errors. This has led to the development of the SFA, which seeks to take into account external factors when estimating the efficiency of the firms.

The nonparametric approach does not require a production function to calculate the efficiency measures. It attempts to determine the efficiency of the firm against some imposed benchmark through mathematical programming. The most common version of this approach is DEA.

We follow the nonparametric approach, DEA, to estimate the production technology frontier for each country in a set of Latin American banking industries. We do not estimate a common frontier because regulatory frameworks differ across countries and because the efficiency measures will be regressed on each country's banking and macroeconomic characteristics.

One advantage of using DEA is that, unlike the SFA, it does not require knowledge of the proper functional form of the frontier, error, and inefficient structure and it is less data demanding, in that it works well with a relatively small sample size (compared to SFA) to make reliable estimations (Bauer, Berger, Ferrier, & Humphrey, 1998; Grifell-Tatjé & Lovell, 1996; Wheelock & Wilson, 1999). Moreover, DEA allows us to calculate Malmquist indices to characterize productivity changes in Latin American banking industries.

We use input-oriented DEA in our estimation because, in general, banking industries have to place more emphasis on controlling cost after liberalization (Berg, Forsund, & Jansen, 1992; Berger & Humphrey, 1997, Isik & Hassan, 2002). Nevertheless, the general tenor of our results does not change when using output-oriented DEA. As a matter of fact, the "choice of using either input- or output-oriented is not crucial as it is in the econometric case" (Coelli, 1996, p. 23). More important, "output- or input-oriented models will estimate exactly the same frontier and, therefore, by definition, identify the same set of decision making units (DMU's) as being efficient" (Coelli, 1996, p. 23).[2] Only the inefficiency scores associated with inefficient DMU's may differ between input-oriented and output-oriented methods.

Data Envelopment Analysis

DEA is a linear programming technique that allows calculating the relative efficiency of a business unit. It was developed by Charnes, Cooper, and Rhodes (1978) in order to measure relative efficiency without knowing a priori what variables are more important or what the relationship among them is.

Consider the CCR model (Charnes et al., 1978). Let us evaluate n banks each one producing different outputs (y) and using different inputs (x). The efficiency of a bank i (TE_i), assuming constant returns to scale (CRS), is measured as follows:

$$Max_{u,v}\ \left(\frac{u' y_i}{v' x_i}\right), \tag{1}$$

Subject to: $\dfrac{u' y_j}{v' x_j} \leq 1;\ \ j = 1, 2, ..., N;$

$u, v > \varepsilon > 0;$

where:

x - vector of bank inputs,

y - vector of bank outputs given the inputs,

u - the weighted relative vector associated to output,

v - the weighted relative vector associated to input,

ε - small positive number ($\varepsilon > 0$).

The original mathematical formulation is not linear. To avoid this problem, the constraint $v' x = 1$ is imposed, which provides the following:

$$Max_{u,v}\ (u' y_i), \tag{2}$$

Subject to: $v' x_i = 1;$

$u' y_j - v' x_j \leq 0;\ \ j = 1, 2, ..., N;$

$u, v > \varepsilon > 0.$

The dual form of the above problem as used in the literature is as follows:

$$Min_{\theta,\lambda}\ \theta, \tag{3}$$

Subject to: $-y_i + Y\lambda \geq 0$;

$\theta X_i - X\lambda \geq 0$;

$\lambda \geq 0$;

where X is $m \times n$ input matrix, Y is $s \times n$ output matrix, λ is a $n \times 1$ vector of intensities and θ is the efficiency score for bank i.

Variables such as imperfect competition and constraints in finance may cause a bank not to operate at the optimal scale. In this case, the CRS assumption that banks are operating at optimal scale may not be appropriate. If the CRS model is used when not all banks are operating at optimal level, the *technical efficiency* (i.e., the CRS efficiency provided by the CCR model) is confounded with *scale efficiency*. Banker, Charnes, and Cooper (1984) suggested an extension of the above model to take into account the variable returns to scale (VRS). Thus, the BCC model (Banker et al., 1984) adds the convexity constraint $1'\lambda = 1$ to the CCR model in order to calculate VRS efficiency, where 1 is a vector of ones. The VRS efficiency is known as *pure technical efficiency* in the literature. Further, the CRS *technical efficiency* may be decomposed into VRS *pure technical efficiency* and *scale efficiency*:

$$TE_{CRS} = TE_{VRS}SE.$$

Therefore, to calculate *scale efficiency*, we must estimate CRS and VRS efficiency upon the same data. If there is any difference between CRS and VRS efficiency, this indicates scale inefficiency, which can be obtained by the proportion CRS technical efficiency to VRS pure technical efficiency.

To calculate VRS cost efficiency, we estimate the following cost minimization problem:

$$Min_{\lambda,x_i^*}\ (w_i'x_i^*), \tag{4}$$

Subject to: $-y_i + Y\lambda \geq 0$;

$x_i^* - X\lambda \geq 0$;

$1'\lambda = 1$;

$\lambda \geq 0$;

where w_i is a vector of input prices for the i^{th} bank and x_i^* is the cost-minimizing of input quantities for the i^{th} bank given the input price w_i and output level y_i. Then, the costs efficiency (CE) of the i^{th} bank is calculated as

$$CE = \frac{w_i'x_i^*}{w_i'x_i}.$$

That is, the ratio of minimum cost to observed cost. The allocative efficiency (AE), therefore, may be obtained by

$$AE = \frac{CE}{TE},$$

where TE is the CRS technical efficiency.

Revenue and profit efficiency are calculated in similar manner, but the optimum is a mix of output that maximizes revenues for the case of revenue efficiency and a mix of output and input that maximizes profit. Cost and revenue efficiencies are bounded between 0 and 1. However, profit efficiency is not bounded (Zhu, 2003):

$$Profit\ efficiency = \frac{(p_i ' y_i - w_i ' x_i)}{(p_i ' y_i^* - w_i ' x_i^*)},$$

where p is a vector of output prices and the asterisks represent optimal level of outputs and inputs. Note that our definition of profit efficiency could lead to negative or higher than 1 efficiency scores.

In summary, using Excel add-ins developed by Zhu (2003), we estimate CRS technical efficiency (CCR model), VRS pure technical efficiency (BCC model), and CRS revenue, cost, and profit efficiency. Moreover, scale efficiency and allocative efficiency are calculated from these efficiency scales.

The Malmquist Index

DEA can be used to calculate a Malmquist index, which measures productivity change that is broken down into *technological change* and *technical efficiency change*. The index may be interpreted as an index of TFP. It takes into account whether firms are showing improvement in their use of resources to produce goods and services, and whether the existing technology has shifted. Values greater than 1 indicate increases in productivity, while values less than 1 indicate decreases in productivity over time. The change in *technical efficiency* can be further decomposed into *pure technical change*, which measures whether managers have improved the use of resources, or scale efficiency change, which measures whether banks have moved to an optimal scale relative to the frontier. A change in *scale efficiency* may be caused either by a change in the technology, a change in the location of the bank in the input/output space from one year to another, or a combination of these factors. Changes in *pure technical efficiency* are caused by a movement of the bank relative to the existing technology.

The Malmquist total productivity change index (M) is the product of technical efficiency change (*TEFFCH*), which is how much closer a bank gets to the efficient frontier (catching up), and technological change (*TECHCH*), which is how much the benchmark production frontier shifts (technical innovation). Further, technical efficiency change (*TEFFCH*) is decomposed into pure technical efficiency change (*PTECH*) and scale efficiency change (*SECH*), as shown by Färe, Grosskopf, Norris, and Zhang (1994):

$$M(t,\ t+1) = \overbrace{\underbrace{\left[\frac{D_{t+1}^{VRS}(x_{t+1}, y_{t+1})}{D_t^{VRS}(x_t, y_t)}\right]}_{PTECH} \underbrace{\left\{\frac{\left[\frac{D_{t+1}^{CRS}(x_{t+1}, y_{t+1})}{D_{t+1}^{VRS}(x_{t+1}, y_{t+1})}\right]}{\left[\frac{D_t^{CRS}(x_t, y_t)}{D_t^{VRS}(x_t, y_t)}\right]}\right\}}_{SECH}}^{TEFFCH} \underbrace{\left[\frac{D_t^{CRS}(x_{t+1}, y_{t+1})}{D_{t+1}^{CRS}(x_{t+1}, y_{t+1})} \frac{D_t^{CRS}(x_t, y_t)}{D_{t+1}^{CRS}(x_t, y_t)}\right]^{\frac{1}{2}}}_{TECHCH},$$

where D_s are distant functions (efficiency scores) calculated using DEA. The scores are calculated relative to frontier at time t or $t + 1$.

Empirical Design

In any performance analysis, production units are expected to be relatively homogenous, providing similar services while using similar resources. This study is limited to commercial banks because they are relatively homogenous in each Latin American country. We exclude savings institutions because of their small market share in the sector as well as their significantly different technology, structure, and purpose. Thus, the sample is limited to all commercial banks with information available on the BankScope database during the period 1996-2007. Table 1 summarizes the commercial banks' characteristics in the selected countries.

Table 1
Sample Data

Country	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
Number of banks											
Argentina	83	87	79	73	73	68	64	64	62	61	57
Brazil	130	124	120	120	132	130	113	101	98	98	109
Chile	29	28	27	27	26	25	25	26	25	25	25
Colombia*	29	27	23	24	24	25	25	25	19	15	14
Ecuador	36	36	32	34	33	31	30	29	29	28	25
Mexico*	34	34	34	35	31	34	31	28	26	28	21
Venezuela*	17	21	44	42	35	34	32	33	26	29	12
Concentration											
Argentina	23.60	21.52	20.02	18.98	22.78	26.52	30.47	34.56	36.09	33.86	33.42
Brazil	35.34	37.02	36.00	31.32	31.29	33.29	35.26	32.91	33.39	33.70	35.94
Chile	27.66	24.43	24.24	24.08	24.17	35.95	33.62	32.66	32.37	32.90	32.05
Colombia	39.27	36.57	37.18	36.02	36.86	38.48	37.07	38.49	43.91	49.16	51.95
Ecuador	39.41	38.98	43.44	30.19	34.09	46.11	46.60	46.46	43.58	52.05	56.52
Mexico	45.56	42.91	35.80	40.71	44.77	41.17	46.98	41.70	61.52	57.76	58.63
Venezuela	34.06	32.59	34.45	30.81	30.33	27.56	28.76	25.44	24.29	26.22	
Median total assets (Million real 2000 US$)											
Argentina	261.80	229.60	165.70	118.40	108.70	100.20	129.50	203.60	209.10	248.50	274.10
Brazil	423.00	449.40	491.20	452.10	551.80	560.70	661.80	689.60	836.10	834.10	849.10
Chile	606.60	707.90	810.30	1 535.10	1 478.40	791.00	822.40	699.50	681.90	850.30	1 166.00
Colombia	514.20	405.40	573.80	592.90	865.10	1 060.80	1 073.20	1 071.80	1 677.30	2 348.80	2 427.60
Ecuador	119.20	115.60	49.80	32.80	57.60	65.20	75.90	117.60	96.10	114.10	148.50
Mexico	227.50	265.30	360.30	388.70	541.60	483.70	669.00	697.90	745.90	1 109.80	
Venezuela	272.10	206.60	59.60	75.40	118.10	97.20	182.40	340.20	772.80	1 177.60	
Average total assets (Million real 2000 US$)											
Argentina	776.00	838.20	965.70	1 030.10	781.10	1 120.30	1 137.40	1 418.50	1 504.20	1 503.70	1 401.50
Brazil	3 000.60	3 155.30	3 239.90	3 702.30	3 978.50	4 801.10	6 142.70	7 206.60	7 736.40	9 360.90	11 173.90
Chile	2 694.10	3 278.90	3 404.20	3 493.20	3 723.80	4 227.80	4 198.90	4 426.10	4 906.80	5 454.50	6 867.20
Colombia	846.80	805.60	944.70	1 162.00	1 284.40	1 400.00	1 625.20	1 917.50	3 081.00	4 014.90	5 525.60
Ecuador	307.20	298.60	200.10	173.60	244.40	262.20	290.30	352.40	428.30	471.30	540.60
Mexico	3 341.60	3 551.30	4 316.30	4 695.60	5 084.70	5 297.50	5 491.50	6 854.40	5 987.20	6 468.40	10 241.10
Venezuela	345.00	383.60	246.70	368.80	393.60	444.80	669.60	1 057.10	1 676.40	2 482.60	4 415.50

Note. (a) The table shows the number of banks with available data from BankScope. (b) Concentration is defined as total assets of the three biggest banks over total assets in the country. Size is measured by total assets in U.S. dollars. (c) * The drop in the number of banks in 2007 is because data is not available as of June 2008.

Panel A shows the number of banks per country per year. In the sample, Brazil has the most banks followed by Argentina, while the other five countries have roughly the same number of banks. The overall number of banks in Argentina has declined over the sample period because of mergers, acquisitions, and the closure of bankrupted banks as a result of the Argentinean reforms in 2002. Interestingly, the number of banks in Venezuela increased during President Chavez's tenure (1999-2007) as a result of social policies that led to the opening of new banks.

As in many developing countries, Latin American countries have highly concentrated banking industries. Panel B shows the level of concentration in each country, defined as the three largest banks' assets over total assets of all commercial banks. Mexico has the highest level of concentration, with the three biggest banks accounting for around 50% of the total banking assets in the country. The level of concentration in Brazil is high relative to the number of banks, an indication that many Brazilian banks are small. We also note that concentration has increased over the sample period in all countries but Venezuela. We discuss concentration as a characteristic of the countries' financial structure later in this paper.

Because of the high level of concentration, it is important to compare each country's banking industry by median total assets, rather than average assets. Panel C shows the median bank size, measured as total assets in millions of U.S. dollars. Despite the differences in number of banks and level of concentration, median bank size does not vary across the sample nearly as much as average bank size, with the exception of Ecuador which has the lowest median. We also note that, by looking at the first and third quartile (not reported) and with the exception of Ecuador, all countries have quantitatively similar bank size distributions.

Definition of Data

A set of inputs and outputs is needed in order to measure the efficiency and, therefore, the relative productivity of our sample banks using DEA. There are two main approaches to measure efficiency: the *production approach* and the *intermediation approach*. In the first approach, outputs may be measured as number of bills or processed transactions and inputs are measured as capital or labor force, but not as interest expenses. In contrast, the second approach assumes that banks are considered brokers, who transform financial resources into profits. This approach is more commonly used in the study of banking efficiency, and, therefore, we adopt the intermediation approach in this study. Accordingly, we model commercial banks as multiproduct firms, producing three outputs and employing three inputs. All variables are measured in millions of 2000 U.S. dollars, except for the prices which are measured as ratios.

The output vector includes: (a) net loans [*LOANS*]; (b) off-balance-sheet items [*OFF_BS*], including guarantees and warranties (letters of guarantee, bank acceptances, letters of credit, guaranteed pre-financing, endorsements, and others), commitments, foreign exchange, and interest rate transactions as well as other off-balance-sheet activities; and (c) other earning assets [*OTHER_EA*], which consist of loans to special sectors, interbank funds, and investment securities (treasury bills, government bonds, and other securities). All output prices are estimated as proxies, calculated as follows: (a) price of the loans [*P*(*LOANS*)] is the total interest income over net loans, (b) price of other operating income [*P*(*OTHER_EA*)] is defined as other operating income over other earning assets, and (c) price of off-balance-sheet items [*P*(*OFF_BS*)] is other operating income over off-balance-sheet items. Because of data availability, we allocate other operating income according to the weights of other earning assets and off-balance-sheet items in order to avoid double counting of other operating income. Our results are robust to this assumption.

The inputs vector includes: (a) loanable funds [*FUNDS*], the sum of deposit (demand and time) and nondeposit funds as of the end of the respective year; (b) book value of premises and fixed assets [*FIXED_A*]; and (c) overhead [*OVERHEAD*]. We used overhead, which includes personnel expenses and other administrative expenses, to proxy for labor because many banks in our sample do not report personnel expenses in their financial statements. The price of funds [*P*(*FUNDS*)] is calculated as total interest expenses over loanable funds, while the price of capital [*P*(*CAPITAL*)] is the ratio of loan loss provisions to total fixed assets and the price of overhead [*P*(*OVERHEAD*)] is set to 1. Thus, we estimate DEA revenue, cost and profit efficiency scores based on:

Revenue = f (interest income, other operating income);

Cost = f (interest expenses, overhead, loan loss provision);

and *Operating Profit = Revenue – Cost.*

Although our definitions of bank outputs and inputs are not free of shortcomings, we believe that they capture the essence of banking production in Latin America. First, loanable funds, capital, and labor are typically used as inputs for the intermediation approach (see, for instance, Bonin, Hasan, & Watchtel, 2005; Isik & Hassan, 2002). Second, loans and other earning assets are included as output because the former is essential to intermediation as the generator of interest income and the latter have become an important source of income generation in many countries, including Latin American nations. While loans and other earning assets are obvious outputs, the inclusion of off-balance-sheet items needs a more detailed explanation. Berger and Mester (1997) reported that no earlier frontier study accounted for off-balance-sheet items even though the notional amount sometimes were greater than on-balance-sheet items and banks often made "effective substitute for loans that demand similar information gathering, origination, monitoring and control costs" (Isik & Hassan, 2002, p. 729). Furthermore, the risk weights suggested by the Basle Accord imply that off-balance-sheet items have a similar risk to loans (Berger & Mester, 1997).

Sample Statistics

Table 2 shows summary statistics for outputs and inputs and their respective prices by country (average 1997-2007). Isik & Hassan (2002) argued that off-balance-sheet items are important in estimating efficiency because they represent a significant resource that banks use in their operations. This statement is true, at least for big banks in Latin America, as demonstrated by the high average value of these items. In fact, the average value of off-balance-sheet items is higher than that of other earning assets for all countries in our sample. Moreover, it represents the most valuable output for Argentina, Ecuador, and Venezuela (where it is higher than average loans). Furthermore, in Brazil, Mexico, and Venezuela, the average use of off-balance-sheet items increased significantly over our sample time period. The significantly larger size of these items, as well as large banks' increasing usage, emphasizes the importance of considering assets carried off the balance sheet in efficiency studies. Off-balance-sheet items are a revenue generator for big banks in Latin American banking industries, and the exclusion of this variable in efficiency analysis may cause bias in the results against those banks that are actively involved in such activities (Isik & Hassan, 2002).

Loans represent an important output for estimating bank efficiency because the larger this figure, the larger the interest revenues. In Brazil, Chile, Colombia, and Mexico, loans correspond to the higher proportion of outputs for the average bank, and in all countries, for the median bank. Its magnitude has increased in real terms in all countries.

Although other earning assets represent the lowest proportion of output in Latin American banks, we include this item in the study because it is an important generator of revenues for small banks (Carvallo & Kasman, 2005). Banks that are more involved in interbank activities or direct lending will see this reflected in revenues from other earning assets.

Table 2
Average and Median of Outputs and Inputs

	Argentina	Brazil	Chile	Colombia	Ecuador	Mexico	Venezuela
Panel A: *Output (Millions, 2000 US$)*							
Average							
LOANS	362.50 (+)	1 690.30 (+)	2 200.40 (+)	897.80 (+)	117.70 (+)	2 810.80 (+)	335.20 (+)
OTHER_EA	36.90 (+)	272.90 (+)	62.50 (+)	42.90 (+)	8.50 (+)	139.90 (+)	21.50 (+)
OFF_BS	379.70 (n)	379.20 (+)	513.60 (n)	416.10 (n)	240.20 (n)	311.90 (+)	1 230.50 (+)
Median							
LOANS	56.80 (n)	200.80 (+)	509.60 (n)	582.10 (+)	40.60 (n)	281.10 (+)	87.10 (+)
OTHER_EA	8.60 (+)	25.00 (+)	24.00 (+)	19.60 (+)	2.20 (+)	12.80 (+)	5.20 (+)
OFF_BS	47.50 (+)	30.70 (n)	86.00 (n)	126.20 (n)	74.30 (n)	65.90 (n)	313.50 (+)
Panel B: *Input (Millions, 2000 US$)*							
Average							
FUNDS	722.70 (+)	3 753.40 (+)	2 774.60 (+)	1 274.60 (+)	209.10 (+)	3 913.40 (+)	639.10 (+)
FIXED_A	47.00 (n)	92.20 (+)	60.40 (+)	60.20 (+)	15.40 (n)	142.20 (+)	17.80 (+)
OVERHEAD	47.40 (n)	303.20 (+)	88.00 (+)	105.90 (+)	15.30 (+)	242.40 (+)	49.20 (+)
Median							
FUNDS	145.60 (n)	414.40 (+)	619.00 (n)	951.80 (+)	79.50 (+)	395.40 (+)	181.60 (+)
FIXED_A	7.70 (n)	4.10 (+)	14.00 (n)	36.60 (+)	4.20 (–)	9.20 (+)	6.20 (n)
OVERHEAD	11.00 (n)	30.30 (+)	26.10 (n)	83.60 (+)	5.60 (n)	26.80 (+)	16.90 (+)

Panel C: *Output ratios (prices)*							
Average							
P(LOANS)	0.2927 (n)	0.8602 (–)	0.2196 (n)	0.2139 (–)	0.4066 (n)	0.5191 (n)	0.5244 (n)
P(OTHER_EA)	0.0844 (n)	0.0482 (+)	0.0705 (n)	0.1689 (–)	0.0789 (+)	0.0933 (n)	0.0249 (+)
P(OFF_BS)	0.0804 (+)	0.0344 (n)	0.0561 (n)	0.1341 (–)	0.0677 (+)	0.0817 (n)	0.0245 (+)
Median							
P(LOANS)	0.1968 (n)	0.5343 (–)	0.1484 (–)	0.1772 (–)	0.2288 (–)	0.2994 (n)	0.3744 (n)
P(OTHER_EA)	0.0601 (+)	0.0190 (n)	0.0443 (n)	0.1193 (–)	0.0503 (+)	0.0589 (n)	0.0144 (+)
P(OFF_BS)	0.0600 (+)	0.0159 (n)	0.0417 (n)	0.1104 (–)	0.0463 (+)	0.0585 (+)	0.0143 (+)
Panel D: *Input ratios (prices)*							
Average							
P(FUNDS)	0.0606 (n)	0.1642 (–)	0.0563 (–)	0.0936 (–)	0.1006 (–)	0.1770 (–)	0.0748 (n)
*P(CAPITAL)**	0.0135 (n)	0.0128 (n)	0.0083 (n)	0.0143 (n)	0.0133 (n)	0.0100 (n)	0.0109 (n)
*P(OVERHEAD)**	0.0799 (n)	0.0727 (n)	0.0381 (n)	0.0856 (–)	0.0814 (n)	0.0631 (n)	0.0828 (–)
Median							
P(FUNDS)	0.0456 (n)	0.1416 (–)	0.0506 (–)	0.0689 (–)	0.0633 (–)	0.1389 (–)	0.0557 (n)
P(CAPITAL)	0.0069 (n)	0.0062 (n)	0.0046 (n)	0.0105 (n)	0.0047 (n)	0.0052 (n)	0.0067 (n)
P(OVERHEAD)	0.0676 (n)	0.0603 (n)	0.0291 (n)	0.0752 (–)	0.0713 (–)	0.0503 (n)	0.0799 (–)

Note. (a) The output vector includes: net loans [*LOANS*]; off-balance-sheet items [*OFF_BS*], which includes guarantees and warranties (letter of guarantee, bank acceptance, letters of credit, guaranteed pre-financing, endorsements, and others), commitments, foreign exchange and interest rate transactions as well as other off-balance-sheet activities; other earning assets [*OTHER_EA*], which consist of loans to special sectors, interbank funds, and investment securities (treasury bills, government bonds, and other securities). All output prices are estimated as ratios: price of the loans [*P*(*LOANS*)] is the total interest income over net loans; price of other operating income [*P*(*OTHER_EA*)] is defined as other operating income over other earning assets; price of balance sheet items [*P*(*OFF_BS*)] is other operating income over off-balance-sheet items. Input vector includes: overhead; book value of premises and fixed assets [*FIXED_A*]; loanable funds [*FUNDS*], the sum of deposit (demand and time) and non-deposit funds as of the end of the respective year. Input price for funds [*P*(*FUNDS*)] is calculated as total interest expenses over loanable funds. (b) The ratios overhead to total assets and loan loss provision to total assets are also reported. (c) Signs in parenthesis denote either no change (n), or growth (+), or decline (–) at 5% significant level. (d) * These ratios are reported to compare countries' bank cost performance relative to total assets. The ratios are rescaled to calculate cost functions.

Panels C and D show output and input prices. For obvious reasons, prices charged on loans are higher than prices paid (costs) on funds in all countries (see means and medians) as the intermediation approach would prescribe. Brazil charged the highest interest rate on loans during the period 1997-2007. This is consistent with high average real interest rates observed during the period under study. Mexico and Venezuela also have high interest rates on loans, which may be a consequence of relatively high rates of inflation in these countries over the sample period. The prevalence of these high interest rates on loans may preclude the achievement of good efficiency scores in the Latin American banking system; and, thus, we study whether these variables are negatively related to efficiency in the explanation section.

In Colombia, prices of other earning assets are almost as important as prices of loans, reflecting the importance of this item as a revenue generator for Colombian banks. Moreover, this is only the case for Colombian banks, whereas the other countries in our sample show similar prices for other earning assets. Furthermore, there are significant differences in cost of capital and cost of funds across countries, reflecting the difference in macroeconomic and political structure across Latin America. However, all countries but Chile have similar overhead costs.

Analysis of Efficiency Estimates

We analyze the sources of inefficiency in each country based on the calculated efficiency measures, relative to each country's production frontier. Knowing the sources of inefficiency allows regulators as well as managers to trace a plan to make their respective industries more competitive.

As argued in the literature, the level of *technical efficiency* is related to managerial decisions, while *allocative* efficiency is related to regulatory environment or macroeconomic conditions (Lovell, 1993). In other words, good regulatory and macroeconomic conditions should lead to high allocative efficiency, whereas good managerial practices should lead to high technical efficiency. Cost, revenues, and profit efficiency are calculated assuming constant returns to scale because of the diversity in size in our sample (Berg et al., 1992; Dyson et al., 2001). We also omit profit efficiency that is negative or higher than 1 in the estimation of the average.

Table 3 presents efficiency measures per year and per country. Studies done in the United States of America, Europe, and some developing countries have found profit efficiency to be lower than cost efficiency (Ariff & Can, 2008; Berger & De Young, 2001; Berger & Mester, 1997, 2003; Färe, Grosskopf, & Weber, 2004; Isik & Hassan, 2002; Maudos & Pastor, 2003, among others). We also find that profit efficiency is lower than cost efficiency for all countries in our sample, suggesting that most profit inefficiency is the result of revenue inefficiency. Likewise, revenue efficiency is lower than cost efficiency in all countries, confirming that indeed, profit inefficiency may be a consequence of revenue inefficiency.

Further decomposition of revenue efficiency suggests that the source of inefficiency in the sample is regulatory rather than managerial because revenue allocative efficiency is lower than technical efficiency. Ecuador and Venezuela have the lowest revenue allocative efficiency.

In Argentina, revenue, cost, and allocative efficiency decreased sharply from 2000 to 2002, which may be explained by an economic crisis that led to the devaluation of the currency in the same year. Moreover, technical efficiency was relatively low, averaging 72% during this period; this 72% means that the average bank could have produced the same level of output using 72% of the resources actually employed. Furthermore, the average revenue allocative efficiency for the period is 76%. This implies that, although managers chose a relatively cost-minimizing mix of inputs and outputs, they wasted resources during the sample period. Furthermore, the decomposition of technical efficiency into pure technical efficiency and scale efficiency shows that averages of these efficiency scores are very similar. Therefore, there is no clear evidence whether the source of inefficiency is from wasting of resources or from banks working at suboptimal scales.

Table 3
Average Efficiency

	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Ave.
CRS profit efficiency												
Argentina	0.44	0.32	0.33	0.30	0.17	0.30	0.37	0.39	0.37	0.42	0.32	0.34
Brazil	0.11	0.30	0.21	0.25	0.26	0.24	0.23	0.25	0.30	0.27	0.20	0.24
Chile	0.61	0.58	0.57	0.48	0.42	0.33	0.51	0.48	0.45	0.55	0.44	0.49
Colombia	0.39	0.30	0.35	0.34	0.54	0.42	0.34	0.54	0.59	0.60	0.58	0.46
Ecuador	0.60	0.58	0.56	0.72	0.68	0.54	0.56	0.61	0.63	0.64	0.55	0.60
Mexico	0.40	0.36	0.43	0.25	0.50	0.39	0.43	0.34	0.42	0.30	0.47	0.39
Venezuela	0.73	0.50	0.19	0.15	0.25	0.27	0.39	0.20	0.24	0.28	0.66	0.30
CRS revenue efficiency												
Argentina	0.71	0.63	0.63	0.56	0.41	0.51	0.60	0.45	0.48	0.49	0.43	0.55
Brazil	0.23	0.42	0.37	0.40	0.36	0.44	0.26	0.45	0.43	0.43	0.37	0.38
Chile	0.72	0.74	0.71	0.69	0.65	0.38	0.57	0.51	0.67	0.67	0.66	0.64
Colombia	0.49	0.54	0.50	0.61	0.74	0.73	0.70	0.74	0.80	0.85	0.85	0.67
Ecuador	0.81	0.77	0.72	0.63	0.65	0.33	0.47	0.42	0.46	0.43	0.38	0.57
Mexico	0.64	0.63	0.67	0.52	0.57	0.59	0.56	0.51	0.40	0.46	0.47	0.56
Venezuela	0.84	0.74	0.41	0.34	0.32	0.26	0.31	0.13	0.14	0.13	0.73	0.35
CRS cost efficiency												
Argentina	0.64	0.57	0.62	0.51	0.52	0.54	0.57	0.49	0.53	0.60	0.49	0.56
Brazil	0.21	0.47	0.39	0.47	0.42	0.44	0.34	0.44	0.51	0.49	0.38	0.41
Chile	0.83	0.75	0.74	0.75	0.77	0.73	0.67	0.62	0.75	0.77	0.69	0.74
Colombia	0.74	0.72	0.76	0.61	0.72	0.75	0.76	0.82	0.85	0.86	0.85	0.76
Ecuador	0.78	0.79	0.74	0.73	0.72	0.67	0.72	0.68	0.70	0.61	0.69	0.72
Mexico	0.76	0.80	0.74	0.64	0.65	0.64	0.67	0.65	0.68	0.67	0.62	0.69
Venezuela	0.84	0.72	0.34	0.29	0.46	0.35	0.69	0.56	0.59	0.61	0.79	0.52

Revenue allocative efficiency												
Argentina	0.86	0.81	0.82	0.85	0.62	0.74	0.81	0.69	0.70	0.70	0.68	0.76
Brazil	0.63	0.67	0.69	0.68	0.66	0.75	0.58	0.69	0.67	0.67	0.68	0.67
Chile	0.79	0.84	0.83	0.80	0.76	0.45	0.64	0.64	0.79	0.80	0.82	0.74
Colombia	0.58	0.63	0.57	0.69	0.83	0.84	0.84	0.83	0.84	0.88	0.90	0.75
Ecuador	0.91	0.89	0.83	0.70	0.75	0.42	0.55	0.51	0.53	0.48	0.46	0.65
Mexico	0.79	0.73	0.80	0.70	0.76	0.78	0.75	0.65	0.52	0.63	0.59	0.71
Venezuela	0.92	0.86	0.84	0.79	0.50	0.53	0.39	0.18	0.16	0.16	0.82	0.54
Cost allocative efficiency												
Argentina	0.77	0.72	0.79	0.74	0.77	0.79	0.76	0.73	0.77	0.82	0.71	0.76
Brazil	0.57	0.76	0.74	0.77	0.75	0.76	0.69	0.65	0.77	0.76	0.69	0.72
Chile	0.91	0.85	0.86	0.86	0.89	0.85	0.75	0.76	0.89	0.92	0.86	0.86
Colombia	0.88	0.84	0.85	0.69	0.80	0.85	0.91	0.93	0.90	0.89	0.91	0.85
Ecuador	0.87	0.91	0.86	0.82	0.82	0.82	0.84	0.78	0.79	0.64	0.82	0.82
Mexico	0.93	0.93	0.89	0.86	0.87	0.85	0.85	0.80	0.87	0.89	0.77	0.87
Venezuela	0.92	0.83	0.67	0.68	0.76	0.62	0.88	0.79	0.85	0.85	0.90	0.77
Technical efficiency (CRS)												
Argentina	0.82	0.78	0.76	0.67	0.65	0.68	0.76	0.69	0.71	0.73	0.67	0.72
Brazil	0.40	0.63	0.54	0.62	0.57	0.58	0.50	0.68	0.67	0.66	0.56	0.58
Chile	0.91	0.89	0.86	0.87	0.86	0.85	0.88	0.78	0.83	0.82	0.79	0.85
Colombia	0.83	0.85	0.88	0.88	0.88	0.87	0.83	0.88	0.95	0.96	0.94	0.88
Ecuador	0.89	0.87	0.85	0.88	0.87	0.80	0.84	0.84	0.84	0.92	0.85	0.86
Mexico	0.81	0.86	0.84	0.73	0.74	0.74	0.77	0.79	0.77	0.74	0.79	0.78
Venezuela	0.92	0.86	0.49	0.44	0.60	0.56	0.79	0.70	0.70	0.73	0.88	0.65
Pure technical efficiency (VRS)												
Argentina	0.91	0.88	0.86	0.84	0.83	0.80	0.85	0.87	0.88	0.89	0.88	0.86
Brazil	0.74	0.81	0.75	0.77	0.77	0.76	0.70	0.81	0.76	0.78	0.69	0.76
Chile	0.96	0.97	0.96	0.98	0.97	0.95	0.94	0.95	0.93	0.93	0.93	0.95
Colombia	0.92	0.93	0.96	0.95	0.96	0.96	0.95	0.96	0.97	0.99	0.98	0.95
Ecuador	0.95	0.94	0.88	0.90	0.94	0.90	0.94	0.95	0.94	0.98	0.94	0.93
Mexico	0.91	0.95	0.92	0.85	0.83	0.87	0.88	0.90	0.88	0.81	0.86	0.88
Venezuela	0.96	0.93	0.75	0.74	0.84	0.78	0.92	0.87	0.96	0.93	0.99	0.85
Scale efficiency												
Argentina	0.90	0.88	0.88	0.80	0.78	0.84	0.90	0.78	0.80	0.82	0.75	0.83
Brazil	0.53	0.77	0.73	0.80	0.74	0.76	0.73	0.86	0.89	0.85	0.85	0.77
Chile	0.95	0.92	0.89	0.89	0.89	0.89	0.94	0.82	0.89	0.88	0.85	0.89
Colombia	0.90	0.91	0.92	0.92	0.92	0.91	0.88	0.92	0.98	0.98	0.96	0.92
Ecuador	0.93	0.93	0.97	0.97	0.93	0.87	0.88	0.87	0.88	0.94	0.89	0.92
Mexico	0.90	0.90	0.91	0.87	0.89	0.87	0.87	0.88	0.87	0.91	0.91	0.89
Venezuela	0.96	0.93	0.69	0.66	0.73	0.73	0.86	0.81	0.72	0.78	0.89	0.77

Note. (a) Efficiency measures are estimated using DEA. All efficiency measures are calculated using input-oriented DEA. (b) *Technical efficiency* refers to a bank's ability to minimize inputs from the given set of output. *Allocative efficiency* is bank ability to use these inputs in optimal proportion given their respective costs. The combination of *allocative efficiency* and *technical efficiency* provides cost efficiency (also called economic efficiency). The *technical efficiency* can be decomposed into two parts, *scale efficiency*, and *pure technical efficiency*. *Pure technical efficiency* refers to the firm's ability to avoid waste by producing as much output as input usage allows. *Scale efficiency* refers to the firm's ability to work at its optimal scale. (c) CRS stands for constant returns to scale whereas VRS stands for variable returns to scale.

Technical efficiency in Brazil averages 58%, driven by both pure technical inefficiency and scale inefficiency. This means that managers are wasting resources and their banks are not working at optimal scale. Moreover, the low revenue allocative efficiency implies that the regulatory framework or economic conditions play important roles in overall economic efficiency in Brazil. In summary, these efficiency estimates suggest that there is room for improvement at the bank level (managers) as well as the regulatory level (policy makers) in Brazil.

The banking industry in Chile has been consistently efficient, averaging 85% in technical efficiency. Chile implemented structural reforms in the 1980s, and it has had a relatively strong and stable macroeconomic environment, which explains the higher revenue and cost allocative efficiency scores. Nevertheless, revenue allocative efficiency is lower than technical efficiency, which implies that the major source of inefficiency is regulatory rather than managerial. The decomposition of technical efficiency into its two components indicates that the major source of inefficiency is scale rather than use of resources.

The main sources of inefficiency in Colombia are profit inefficiency, revenue inefficiency, and revenue allocative inefficiency, driven by revenue allocative (regulatory) rather than technical (managerial) factors. Nevertheless, both cost and revenue allocative efficiency have increased over this decade in contrast with the end of the 1990s with consequent economic inefficiency. Colombia was submerged in a banking crisis in the late 1990s and reforms were implemented. The increasing allocative efficiency (and the subsequent effect on cost, profit, and revenues efficiency) suggests that improvements to the regulatory framework have worked for Colombia. Moreover, pure technical efficiency has been higher than 90% on average, suggesting an improvement in use of resources as well.

In Ecuador, both revenue allocative and technical efficiency dropped in 2002, affecting revenue and profit efficiency. This drop in efficiency was most likely due to the economic and banking crisis of 2001-2002. As a matter of fact, Ecuador implemented a series of reforms to end the crisis, including the dollarization of the economy. Revenue allocative efficiency has not improved since 2002. However, in the following years, technical efficiency recovered to its average level, suggesting improvements in managerial use of resources.

In Mexico, revenue allocative efficiency has been consistently lower than technical efficiency, implying that lower cost, revenue, and profit efficiency is a consequence of external factors rather than managers' misuse of resources.

Venezuela implemented capital controls and fixed its exchange rate in February 2003. The banking system has tripled (in real U.S. dollars) the level of deposits and short-term funds since then. This increase in funds available in the banking system does not have a corresponding increase in level of loans provided. As a result, there has been a significant decrease in both cost and revenue allocative efficiency, which explains the low levels of profit, revenue, and cost efficiency. In other words, the source of economic inefficiency is allocative rather than technical. Banks chose a suboptimal mix of inputs and outputs because of the regulatory framework and macroeconomic conditions. Furthermore, the decomposition of technical efficiency into pure technical efficiency and scale efficiency demonstrates that working at optimal scale is more of a concern than banks wasting resources.

In summary, most sources of inefficiency in our sample of Latin American banking industries appear to be driven by revenue allocative inefficiency. Thus, most Latin American countries confront either a stringent regulatory framework that provides disincentive for economic efficiency or an unhealthy economic environment that forces managers to choose a suboptimal mix of inputs and banking services. Also, the decomposition of technical efficiency into pure technical efficiency and scale efficiency suggests that technical inefficiency in Latin American banks is typically the result of banks working at suboptimal scales rather than wasting resources.

Explaining Banking Efficiency

The efficiency of a banking system depends on bank-level performance, the level of development in the financial system, and the macroeconomic health of the country. We investigate the determinants of Latin American banking efficiency by running the following fixed effects regression for each efficiency estimate:

$$Eff = b'BANK + f'FIN + m'MACRO + t'YEAR + a'COUNTRY + \varepsilon ,$$

where Eff is the efficiency estimate. $BANK$ is a vector comprising the following ratios: loan loss reserves-to-gross loans [*LLR_GR*], equity-to-total assets [*EQ_TA*], net interest margin [*NIM*], return on average assets [*ROAA*], return on average equity [*ROAE*], overhead cost-to-income ratio [*COST_INC*], net loans-to-net funds ratio [*NL_FUND*], the natural logarithm of total assets [*SIZE*]. FIN is a vector of variables containing proxies for financial development: domestic credit to the private sector provided by banks as a percent of GDP [*CREDIT*], the total value of stocks traded as a percent of GDP [*STOCK*], the total assets of the three largest banks divided by the total assets in the country [*CONCENT*], interest rate spread (lending rate minus deposit rate) [*SPREAD*], and the number of banks in the country [*NUMBER*]. *MACRO* is a vector of macroeconomic variables: GDP per capita (real 2000 US$) [*GDPPC*], GDP growth (annual %) [*GROWTH*], inflation from the GDP deflator [*INFLATION*], real interest rate [*REALINT*], gross domestic savings as a percent of GDP [*SAVINGS*], and an interaction variable between the real interest rate and GDP per capita [*RIGDPPC*]. *COUNTRY* and *YEAR* are vectors of dummy variables for the countries and years under study, while *b*, *f*, *m*, *t,* and *a* are the coefficient vectors.

It is interesting for both academics and practitioners to study whether traditional measures of banking performance (*BANK* vector) have any significant relationship to estimated efficiency. The first ratio, loan loss reserves over gross loans, indicates how much of the total portfolio has been provided for but not charged off. Given a similar charge-off policy, the higher the ratio, the poorer the quality of the loan portfolio would be, and the lower the expected efficiency. The equity-to-total assets ratio is a way of looking at capital adequacy (capital risk). The expected sign depends on two factors. First, a highly efficient bank should capitalize its efficiency in higher profits and, hence, retain more earnings as capital (Carvallo & Kasman, 2005) where a positive relationship would be expected. On the other hand, if this ratio has increased because of banks issuing more shares rather than using deposits, a negative relationship is expected (Berger & Mester, 1997).

Net interest margin measures the profitability of assets. High *NIM* is not associated with high efficiency because wider margins suggest lower competition that typically results in lower measures of economic efficiency (Demirgüç-Kunt & Levine, 1996). Thus, we expect a negative relationship between *NIM* and efficiency. Return on average assets and return on average equity are measures of profitability and related to optimal use of resources. We expect a positive relationship between these ratios and efficiency measures. Overhead cost-to-income ratio is a measure of efficiency in profitability; the higher this ratio, the lower is the efficiency expected. Finally, the ratio of net loans to net funds is a proxy for liquidity, and the higher the ratio, the lower the liquidity. However, the correlation between efficiencies and this ratio is positive if the amount of loans helps banks to diversify risk. In contrast, the correlation is negative if the amount of loans increases credit or liquidity risk (e.g., higher rates of nonperforming loans or greater asset-liability duration gaps, respectively; Williams & Nguyen, 2005). Size is included as a control variable, and we expect that bigger banks have higher efficiency measures.

A well-developed financial system (*FIN* vector) should support banking activities making the entire system more efficient (Bossone & Lee, 2004). The ratio of bank domestic credit to private sector output is a measure of financial depth (Levine & Zervos, 1998). The higher this ratio, the higher the financial depth, and, therefore, higher efficiency measures are expected. Capital market efficiency should positively influence banking efficiency. Capital market efficiency depends on the depth, size, and resilience of the markets, which are related to liquidity. Total value of stocks traded as percentage of GDP (Levine & Zervos, 1998) and turnover (Demirgüç-Kunt & Levine, 1996), defined as the value of stock market transactions relative to total market size, are frequently used as a measure of liquidity. However, correlation between turnover and total value of stocks traded as percentage of GDP is 92% in our sample, and, therefore, we use only the latter to proxy for liquidity. We expect a positive relationship between liquidity and efficiency. A high spread is a measure of bank efficiency in intermediation (Demirgüç-Kunt & Huizinga, 1999) and, therefore, a positive relationship is expected. Finally, we do not expect a priori a given sign respecting the number of banks. If the relationship is negative, it would mean that there are too many banks for the banking system during the sample period, while a positive relationship would suggest that adding more banks to the system would improve efficiency.

High profitability may be explained either by market power (oligopoly) or by efficiency. Concentration is a measure of degree of market power in the banking system. If the relationship between concentration and efficiency is negative, it would suggest that market power is driving this relationship. However, if high efficiency is the explanation for high profitability, concentration would be favorable to consumers and a positive relationship is expected (Demirgüç-Kunt & Levine, 2000).

Macroeconomic conditions (*MACRO* vector) affect banking performance. GDP per capita affects many factors related to demand and supply for loans (Carvallo & Kasman, 2005) and, thus, no sign a priori is expected. There is no clear evidence supporting high efficiency during periods of economic growth in a country. In fact, efficiency may decline because the production possibilities frontier could move while banks need time to react to that change. Boyd et al. (2001) found that high inflation reduced the amount of financing to the private sector, while Khan, Senhadji, and Smith (2001) found that low inflation was harmful for the banking systems as well. We expect a negative relationship between inflation and efficiency because of the relatively high inflation rates across Latin America during the 1990s. Real interest rates in the economy should affect the private demand for credit. As real interest rates increase, the subsequent fall in demand for private credit should have a negative effect on banking efficiency. Finally, Jaffe and Levonian (2001) found that the level of savings in the economy was highly related to financial development; thus, we also include this in the vector of macroeconomic variables affecting efficiency.

Sample Statistics

Table 4 shows averages for each explanatory variable by country and, in parentheses, the sign of the slope during the sample period as a proxy for trends. The source for bank-level variables is BankScope, whereas country-level data are from the World Development Indicators 2008 database (World Bank).

Panel A shows measures of bank characteristics. The loan loss reserves-to-gross loans ratio and the ratio of equity to total assets are both significantly higher in Ecuador. Both have increased significantly during the period as a consequence of the Ecuadorian government taking over defaulting banks (the three largest banks) in 2001. All countries except Ecuador and Colombia show similar capital ratios exceeding Basel Accords standards. Net interest margin is extremely high in Venezuela, and it is also high for the other countries (except Ecuador) compared to developed markets. Finally, profitability ratios (*ROAA* and *ROAE*) differ among the sample countries. The negative mean profitability in Ecuador is because of the banking and macroeconomic instability in 2002, whereas the Argentinian mean can be explained by consistent accounting losses from 1997 to 2003, reflecting the critical health of the banking system prior to the crisis of 2002, when Argentina devaluated its currency. Argentina and Mexico present the highest overhead cost-to-income ratios on average (77% and 83%, respectively) with no significant fluctuations during the period. Finally, Argentina, Brazil, and Venezuela show the lowest net loan-to-funds ratios.

Panel B shows the values regarding banking and financial structure. Concentration has significantly increased in Brazil, Chile, and Colombia over the sample period, with the highest level of concentration in Mexico at 60.4% of total assets in the economy controlled by the three largest banks. Nevertheless, this level of concentration is not high by international standards (Beck, Demirgüç-Kunt, & Levine, 2003). Total credit provided by banks to the private sector is highest in Chile, increasing over the period due to its relatively healthy banking and financial system. As mentioned in the previous section, the number of banks in most of the sample countries has declined because of bank closings, mergers, and acquisitions in the last few years. The only exception is Venezuela, which had a decrease in the number of banks at the end of the 1990s, though growth in the industry led to an increase during the first half of the 2000s (with no significant net change).

Chile records the lowest spread on interest rates over the sample period, while Brazil the highest. As for trends, the interest rate spread has been declining in Brazil, Colombia, Ecuador, Mexico, and Venezuela. Venezuela has observed a decline in the size of the stock market relative to GDP, whereas the two countries with relatively healthy economies during the period, Chile and Colombia, have increased the size of the stock market relative to GDP.

Table 4
Averages and Trends for Bank-Level and Country-Level Variables (1997-2007)

	Argentina	Brazil	Chile	Colombia	Ecuador	Mexico	Venezuela
Panel A: *Bank characteristic*							
LLR_GR	9.60 (n)	8.00 (–)	5.30 (n)	5.00 (n)	35.80 (–)	5.50 (n)	7.30 (n)
EQ_TA	21.40 (n)	20.00 (n)	19.60 (n)	12.60 (–)	16.40 (n)	18.10 (n)	21.10 (n)
NIM	7.40 (n)	12.60 (n)	5.60 (n)	6.00 (n)	7.50 (–)	6.20 (+)	16.10 (–)
ROAA	-0.80 (n)	2.30 (n)	0.90 (n)	0.60 (+)	1.60 (n)	0.50 (+)	4.10 (n)
ROAE	-4.90 (n)	12.00 (n)	8.00 (n)	3.10 (+)	11.40 (+)	4.20 (+)	25.20 (n)
COST_INC	77.50 (n)	33.90 (+)	41.70 (n)	49.90 (n)	50.80 (+)	83.20 (n)	47.40 (n)
NL_FUND	39.20 (n)	35.90 (+)	55.70 (n)	59.60 (n)	49.50 (n)	52.60 (–)	39.10 (n)
Panel B: *Banking and financial structure*							
CREDIT	17.60 (–)	35.20 (n)	75.50 (+)	32.00 (n)	26.10 (–)	20.10 (n)	13.40 (n)
STOCK	3.90 (n)	18.10 (n)	11.50 (+)	2.40 (+)	0.40 (n)	8.30 (n)	0.90 (–)
CONCENT	37.10 (n)	40.20 (+)	52.70 (+)	38.60 (+)	50.30 (n)	60.40 (n)	45.00 (n)
SPREAD	5.00 (n)	44.60 (–)	4.00 (n)	7.80 (–)	8.40 (–)	6.90 (–)	8.10 (–)
NUMBER	71.80 (–)	120.30 (–)	25.80 (–)	23.60 (–)	31.90 (–)	31.00 (–)	29.40 (n)
Panel C: *Macroeconomical conditions*							
GDPPC (Th)	7.79 (n)	3.80 (+)	5.20 (+)	2.13 (+)	1.43 (+)	5.85 (+)	4.91 (n)
GROWTH	3.50 (n)	2.70 (+)	4.30 (n)	3.00 (+)	3.20 (+)	3.70 (n)	3.20 (n)
INFLATION	6.90 (+)	8.40 (–)	5.20 (+)	9.60 (–)	4.20 (+)	11.10 (–)	33.30 (–)
REALINT	8.10 (–)	52.60 (–)	5.90 (–)	11.80 (–)	18.80 (–)	3.90 (n)	-2.80 (n)
SAVINGS	22.00 (+)	17.90 (+)	26.80 (+)	16.80 (+)	21.40 (n)	21.20 (–)	35.10 (+)

Note. (a) This table shows average and trends for explanatory regression variables. (b) Loan loss reserves to gross loans [*LLR_GR*], equity to total assets [*EQ_TA*], net interest margin [*NIM*], return on average assets [*ROAA*], return on average equity [*ROAE*], overhead cost to total operating income ratio [*COST_INC*], domestic credit provided by banks (% of GDP) [*CREDIT*], total stocks traded relative to GDP [*STOCK*], concentration – the total assets of the three biggest banks over total assets in the country [*CONCENT*], interest rate spread (lending rate minus deposit rate) [*SPREAD*], number of banks in the country [*NUMBER*], GDP per capita (constant thousands, U.S. dollars) [*GDPPC*], GDP growth (annual %) [*GROWTH*], inflation from the GDP deflator [*INFLATION*], real interest rate [*REALINT*], and gross domestic savings (% of GDP) [*SAVINGS*]. (c) The sign in parentheses indicates whether the variable has increased or not, on average, during the period at a 5% level of significance. (d) The source for bank-level variables is BankScope, while country-level data are from the WDI database (World Bank).

Analysis of the Regression Results

We perform country and year fixed-effects regressions of the estimated efficiency measures on the set of bank characteristic variables, financial structure variables, and macroeconomic variables. We use Tobit (censored) regressions with boundaries of 0 at the left and 1 at the right.

A problem with DEA profit efficiency is that the estimated efficiency could be negative or higher than 1. The possibility of having negative profit efficiency has been discussed in the literature. For instance, Cooper, Seiford, and Tone (2000) pointed out that ratio of observed profits to optimal profits would be a problem if observed profit was negative. Nevertheless, other authors have argued that negative profit efficiency is not a problem because firms "can throw away more than 100 percent of the profits" (Berger & Mester, 1997). We avoid negative profit efficiency by using Tobit censored regression, and yet we use the information (negative profits) to get consistent estimates of the parameters.

Table 5 reports the results of the Tobit regressions. Regarding bank characteristics, the ratio of loan loss reserves to gross loans is negatively related to efficiency measures. As expected, banks with low quality loan portfolios tend to have low efficiency. Also, the equity-to-total asset ratio is significant and positively associated with all efficiency scales except cost allocative efficiency. Carvallo and Kasman (2005) also found a positive association between cost efficiency and the equity-to-total asset ratio for Latin American countries. Many Latin American banks do not get involved in issuing shares because they are not publicly traded, or they are subsidiaries of foreign or government banks. Thus, this result suggests that efficient Latin American banks capitalize earnings in equity.

Table 5a

Determinant of Banking Efficiency in Latin America

	TE	PTE	SE	CAE	RAE	CE	RE	PE
Bank characteristics								
LLR_GR	-0.011**	-0.008	-0.004	-0.008*	-0.005	-0.015***	-0.012*	-0.035***
	(0.005)	(0.005)	(0.004)	(0.005)	(0.007)	(0.005)	(0.006)	(0.012)
EQ_TA	0.431***	0.771***	0.061**	-0.064**	0.115***	0.211***	0.399***	0.822***
	(0.037)	(0.043)	(0.030)	(0.027)	(0.040)	(0.031)	(0.035)	(0.074)
NIM	-0.769***	-0.527***	-0.531***	-0.371***	0.145**	-0.686***	-0.346***	-0.401***
	(0.046)	(0.047)	(0.036)	(0.038)	(0.058)	(0.044)	(0.050)	(0.108)
ROAA	0.437***	-0.016	0.352***	0.549***	0.049	0.663***	0.256**	1.250***
	(0.103)	(0.115)	(0.082)	(0.082)	(0.125)	(0.096)	(0.108)	(0.323)
ROAE	0.028*	0.051***	0.025**	-0.012	0.029	0.020	0.050***	0.640***
	(0.015)	(0.016)	(0.012)	(0.012)	(0.019)	(0.014)	(0.016)	(0.071)
NL_FUND	0.162***	0.286***	0.063***	0.011***	0.004***	0.020***	0.004***	-0.0004
	(0.011)	(0.016)	(0.008)	(0.002)	(0.001)	(0.003)	(0.001)	(0.0007)
COST_INC	-0.283***	-0.086***	-0.224***	-0.185***	-0.372***	-0.367***	-0.520***	-0.135**
	(0.030)	(0.032)	(0.024)	(0.024)	(0.036)	(0.028)	(0.031)	(0.067)
SIZE	-0.002	0.093***	-0.053***	0.016***	0.002	0.006**	0.001	0.002
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.003)	(0.003)	(0.007)

Note. (a) The censored regression (Tobit) is estimated with country and year fixed-effects, and covers the period 1997-2007. All dependent variables are censored at the left (0) and at the right (1). (b) The independent variables are constant returns to scale (CRS), technical efficiency (TE), VRS pure technical efficiency (PTE), scale efficiency (SE), cost allocative efficiency (CAE), CRS cost efficiency (CE), CRS revenue allocative efficiency (RAE), CRS revenue efficiency (RE), and CRS profit efficiency (PE). Variables' definitions can be found at Table 4. *RIGDPPC*: interaction variable of real interest rate and GDP per capita. (c) The number of observations is 3398 year-banks from seven Latin American countries. (d) The *, **, and *** denote significance at 10, 5, and 1%, respectively. Standard errors are shown in parentheses.

Table 5b

Determinant of Banking Efficiency in Latin America

	TE	PTE	SE	CAE	RAE	CE	RE	PE
Banking and financial structure								
CREDIT	0.033	-0.137	0.198**	-0.165*	-0.665***	-0.191*	-0.481***	-0.707***
	(0.109)	(0.124)	(0.088)	(0.091)	(0.137)	(0.105)	(0.119)	(0.249)
STOCK	-0.521***	-0.076	-0.474***	-0.115	0.840***	-0.353***	0.359**	-0.529*
	(0.130)	(0.147)	(0.104)	(0.107)	(0.162)	(0.124)	(0.141)	(0.289)
CONCENT	-0.393***	-0.200	-0.216**	-0.106	-0.541***	-0.338***	-0.833***	-0.057
	(0.132)	(0.147)	(0.106)	(0.109)	(0.165)	(0.127)	(0.144)	(0.294)
SPREAD	0.672**	1.543***	-0.321	-0.322	0.208	-0.029	0.406	0.749
	(0.266)	(0.293)	(0.213)	(0.220)	(0.334)	(0.255)	(0.290)	(0.602)
NUMBER	-0.655***	-0.407***	-0.559***	-0.092	-0.552***	-0.487***	-0.791***	-0.457**
	(0.081)	(0.090)	(0.065)	(0.067)	(0.102)	(0.078)	(0.089)	(0.180)

Note. (a) The censored regression (Tobit) is estimated with country and year fixed-effects, and covers the period 1997-2007. All dependent variables are censored at the left (0) and at the right (1). (b) The independent variables are constant returns to scale (CRS), technical efficiency (TE), VRS pure technical efficiency (PTE), scale efficiency (SE), cost allocative efficiency (CAE), CRS cost efficiency (CE), CRS revenue allocative efficiency (RAE), CRS revenue efficiency (RE), and CRS profit efficiency (PE). Variables' definitions can be found at Table 4. *RIGDPPC*: interaction variable of real interest rate and GDP per capita. (c) The number of observations is 3398 year-banks from seven Latin American countries. (d) The *, **, and *** denote significance at 10, 5, and 1%, respectively. Standard errors are shown in parentheses.

Table 5c
Determinant of Banking Efficiency in Latin America

	TE	PTE	SE	CAE	RAE	CE	RE	PE
Macroeconomical variables								
GDPPC	-0.079***	-0.069**	-0.040**	-0.076***	-0.035	-0.091***	-0.061**	-0.065
	(0.025)	(0.027)	(0.020)	(0.020)	(0.031)	(0.023)	(0.027)	(0.055)
GROWTH	-0.056	-0.297	0.065	0.297*	-0.695***	0.163	-0.345*	-1.019**
	(0.183)	(0.199)	(0.147)	(0.152)	(0.231)	(0.176)	(0.201)	(0.414)
REALINT	-1.091***	-0.898***	-0.699***	0.115	-0.043	-0.599***	-0.571***	-0.897***
	(0.151)	(0.168)	(0.121)	(0.124)	(0.188)	(0.144)	(0.164)	(0.337)
INFLATION	-0.934***	-0.933***	-0.487***	0.164	-0.517**	-0.351**	-0.865***	-1.242***
	(0.168)	(0.186)	(0.135)	(0.139)	(0.210)	(0.161)	(0.183)	(0.381)
SAVINGS	0.235	0.256	0.294	0.301	0.879***	0.410	0.854***	-0.164
	(0.270)	(0.296)	(0.217)	(0.222)	(0.337)	(0.257)	(0.293)	(0.608)
RIGDPPC	0.030	-0.061**	0.087***	-0.008	-0.121***	0.043*	-0.047	-0.134**
	(0.027)	(0.029)	(0.022)	(0.022)	(0.034)	(0.026)	(0.030)	(0.062)
Sigma	0.23	0.22	0.18	0.19	0.30	0.23	0.26	0.50

Note. (a) The censored regression (Tobit) is estimated with country and year fixed-effects, and covers the period 1997-2007. All dependent variables are censored at the left (0) and at the right (1). (b) The independent variables are constant returns to scale (CRS), technical efficiency (TE), VRS pure technical efficiency (PTE), scale efficiency (SE), cost allocative efficiency (CAE), CRS cost efficiency (CE), CRS revenue allocative efficiency (RAE), CRS revenue efficiency (RE), and CRS profit efficiency (PE). Variables' definitions can be found at Table 4. *RIGDPPC*: interaction variable of real interest rate and GDP per capita. (c) The number of observations is 3398 year-banks from seven Latin American countries. (d) The *, **, and *** denote significance at 10, 5, and 1%, respectively. Standard errors are shown in parentheses.

NIM is significant and negatively related to efficiency estimates, with the exception of revenue allocative efficiency. These results confirm previous findings for Brazil and Venezuela (Herrero, Santillan, Gallego, Cuadro, & Egea, 2002) and correspond with the view that wider margins suggest less competition, resulting in lower economic efficiency (Demirgüç-Kunt & Levine, 1996). Profitability ratios, *ROAA* and *ROAE*, are positively related to greater efficiency (e.g., more efficient banks tend to earn more), confirming previous findings for Latin American banking industry (Chortareas et al., 2011) and Turkish banking industry (Isik & Hassan, 2002), as well as findings for developed banking industries (Berger & Humphrey, 1997). The ratio of net loans to net funds is positively correlated with all efficiency measures, suggesting that either net loans allow efficient banks to diversify risk or that efficient banks are the ones engaging in aggressive lending. As expected, the overhead cost-to-income ratio is negatively related to efficiency, implying that efficient banks have lower overhead costs. Finally, size is positively associated with cost efficiency, cost allocative efficiency, and pure technical efficiency and negatively associated with scale efficiency. The former results verify previous findings by Carvallo and Kasman (2005); bigger Latin American banks tend to be more cost efficient and tend to use banks' resources more efficiently (pure technical efficiency). However, bigger banks also tend to be working at suboptimal scale. In summary, efficient banks have lower overhead cost relative to total income, use resources better, have higher quality portfolios, and have higher earnings (e.g., higher ROA and ROE) than inefficient ones.

Demirgüç-Kunt and Huizinga (1999) argued that spread is a measure of banking efficiency in intermediation. Furthermore, Levine and Zervos (1998) advocated the use of total value of stocks traded as percentage of GDP and domestic credit provided by banks as proxies for depth, size, and resilience of the markets.

We find that interest rate spreads are positively associated with technical and pure technical efficiency, as expected. Domestic credit provided by banks to the private sector is negatively associated with all efficiency measures, except scale efficiency. Bossone and Lee (2004), using a sample of 975 banks in 75 countries, also found that financial depth is positively related to scale efficiency. However, contrary to our hypothesis, we find that economic efficiency (cost, revenue, profit) and allocative efficiency is negatively related to credit provided by banks to the private sector. Likewise, we find that technical, cost, and profit efficiency is negatively associated with the value of stocks traded as percentage of GDP. This means that Latin American banks working in more developed stock markets tend to choose a suboptimal mix of output services, most likely because they compete in very small capital markets. Nevertheless, the competition provides an incentive to choose a revenue-maximizing mix of outputs and inputs as shown by the positive association between revenue efficiency and stock traded. It appears that underdeveloped capital markets in Latin American countries negatively affect economic efficiency.

High concentration diminishes banking efficiency. These results support the view that greater concentration may result in lower competition and, thus, lower efficiency. Finally, the number of banks in Latin American countries is negatively related to efficiency, suggesting that there are too many banks in the banking system. These results suggest that policy makers should provide incentives for the reduction in the number of banks in Latin American countries but avoid the increase of concentration.

Regarding macroeconomic variables, the level of savings is positively related to revenue allocative and revenue efficiency. GDP per capita is negatively related to efficiency, confirming previous findings for Latin American countries (Carvallo & Kasman, 2005).

High inflation reduces the amount of financing to the private sector (Boyd et al., 2001), and high real interest rates affect the demand for credit. We find negative correlation between these variables and efficiency, as expected. The interaction between real interest rates and GDP per capita shows that efficiency decreases when there is an increase in real interest rates for high GDP per capita in Latin American countries. Finally, regarding economic growth, we find positive correlation between growth and cost allocative efficiency and negative correlations with revenue and profit efficiencies.

Malmquist Productivity Change in the Latin American Banking Industry

In order to estimate Malmquist indexes, balanced panel data are needed. This represents a drawback in the estimation because only surviving banks, i.e., banks with complete data during the period, must be used. Nevertheless, the estimation of Malmquist indexes is still informative because the performance of best practice banks is likely to represent country behavior. In addition, the indexes allow us to examine how banks reacted to the reforms implemented to escape crisis and foster growth.

Table 6 shows the indexes per year as well as the compounded growth for the period 1997-2007 in each country, while Table 7 indicates either improvement (+), status quo (0), or deterioration (–) of the indexes. The reference frontier is fixed at 1997. The first important observation in Table 7 is that banking industries in all countries but Mexico showed technological progress during the period 1997-2007, with Ecuador and Venezuela showing the greatest change in the use of technology (65.7% and 21.9% per year, respectively). This technological progress suggests that Latin American banks have been investing heavily in technology.

Argentina's total productivity change over the sample period was 6.2%, averaging 0.6% per year. This increase in productivity is due to incremental change in the use of technology, though this was partially offset by the decrease in technical efficiency (3.9%). Argentina has experienced technological growth since 2003, showing more than 9% in two consecutive years (2004 and 2005). This change in technology is also correlated with the high economic growth observed in the country after the 2002 reforms.

Technical efficiency was stagnant in Brazil, though a 4.7% gain in technology results in a 4.7% increase of total productivity over the period 1997-2007. The stagnation in technical efficiency suggests that inefficient banks have not been able to catch up with efficient Brazilian banks.

Table 6
Malmquist Indexes

	Technical efficiency change	Technological change	Pure technical efficiency change	Scale efficiency change	Total factor productivity change
Panel A: *Argentina*					
1997-1998	0.947	1.017	0.959	0.988	0.963
1998-1999	0.984	0.983	0.974	1.010	0.967
1999-2000	0.954	0.905	0.993	0.961	0.863
2000-2001	1.071	1.091	1.016	1.054	1.169
2001-2002	0.999	0.794	1.002	0.997	0.793
2002-2003	0.996	1.030	1.014	0.983	1.026
2003-2004	1.044	1.098	1.035	1.008	1.146
2004-2005	1.003	1.096	0.990	1.013	1.099
2005-2006	1.002	1.056	1.000	1.002	1.058
2006-2007	0.965	1.083	1.009	0.957	1.045
Geometric mean	**0.996**	**1.010**	**0.999**	**0.997**	**1.006**
Cumulative 1997-2007	**0.961**	**1.105**	**0.990**	**0.970**	**1.062**
Panel B: *Brazil*					
1997- 1998	1.118	0.889	1.066	1.049	0.994
1998-1999	0.917	1.039	0.957	0.958	0.952
1999-2000	1.056	1.007	1.049	1.007	1.064
2000-2001	0.934	1.152	0.941	0.993	1.076
2001-2002	0.995	0.947	0.992	1.003	0.942
2002-2003	0.995	0.948	0.998	0.996	0.943
2003-2004	1.061	1.015	1.035	1.025	1.077
2004-2005	1.016	0.974	0.989	1.026	0.989
2005-2006	1.009	0.950	1.007	1.001	0.959
2006-2007	0.922	1.152	0.974	0.947	1.062
Geometric mean	**1.000**	**1.004**	**1.000**	**1.000**	**1.004**
Cumulative 1997-2007	**1.000**	**1.041**	**1.000**	**1.000**	**1.041**
Panel C: *Chile*					
1997-1998	0.958	0.976	1.002	0.957	0.935
1998-1999	0.974	1.024	1.000	0.974	0.997
1999-2000	1.002	1.082	1.012	0.990	1.084
2000-2001	1.032	0.968	0.990	1.043	0.999
2001-2002	0.971	1.409	1.007	0.964	1.368
2002-2003	1.036	0.808	0.981	1.056	0.837
2003-2004	0.981	0.793	1.008	0.974	0.779
2004-2005	0.993	1.081	1.000	0.993	1.074
2005-2006	1.015	0.977	1.012	1.003	0.992
2006-2007	1.017	1.194	1.000	1.016	1.214
Geometric mean	**0.998**	**1.018**	**1.001**	**0.996**	**1.015**
Cumulative 1997-2007	**0.980**	**1.195**	**1.010**	**0.961**	**1.161**
Panel D: *Colombia*					
1997-1998	0.985	0.935	0.995	0.990	0.921
1998-1999	0.999	0.772	1.001	0.998	0.771
1999-2000	0.998	1.145	1.005	0.993	1.143
2000-2001	1.010	1.050	1.000	1.010	1.060
2001-2002	1.000	1.087	1.002	0.998	1.087
2002-2003	0.985	1.035	0.988	0.997	1.019
2003-2004	1.009	1.072	1.003	1.006	1.081
2004-2005	0.999	1.036	0.988	1.012	1.035
2005-2006	1.002	0.963	1.017	0.986	0.965
2006-2007	0.966	1.067	0.992	0.974	1.031
Geometric mean	**0.995**	**1.011**	**0.999**	**0.996**	**1.006**
Cumulative 1997-2007	**0.951**	**1.116**	**0.990**	**0.961**	**1.062**

Panel E: *Ecuador*					
1997-1998	1.028	1.098	1.023	1.005	1.129
1998-1999	1.015	1.015	1.008	1.007	1.030
1999-2000	1.057	1.107	1.029	1.027	1.171
2000-2001	0.924	1.076	0.986	0.937	0.994
2001-2002	1.035	0.893	0.983	1.053	0.925
2002-2003	0.991	1.140	1.009	0.982	1.130
2003-2004	1.009	1.074	1.015	0.995	1.084
2004-2005	1.020	1.057	0.994	1.026	1.078
2005-2006	0.977	1.039	0.987	0.991	1.015
2006-2007	0.998	0.995	1.011	0.987	0.993
Geometric mean	**1.005**	**1.047**	**1.004**	**1.000**	**1.052**
Cumulative 1997-2007	**1.056**	**1.657**	**1.045**	**1.000**	**1.747**
Panel F: *Mexico*					
1997-1998	1.081	0.820	1.018	1.062	0.887
1998-1999	0.921	1.065	0.988	0.932	0.981
1999-2000	0.884	1.240	0.959	0.922	1.097
2000-2001	1.003	0.827	1.000	1.002	0.829
2001-2002	1.026	1.070	0.979	1.048	1.098
2002-2003	1.085	0.947	1.030	1.053	1.027
2003-2004	1.061	0.887	1.029	1.031	0.941
2004-2005	1.022	0.917	1.004	1.017	0.937
2005-2006	0.998	1.104	0.983	1.015	1.102
2006-2007	0.997	1.126	1.004	0.993	1.123
Geometric mean	**1.003**	**0.990**	**0.997**	**1.005**	**0.992**
Cumulative 1997-2007	**1.030**	**0.904**	**0.970**	**1.051**	**0.923**
Panel G: *Venezuela*					
1997-1998	0.977	0.789	0.997	0.980	0.771
1998-1999	0.966	0.920	0.970	0.996	0.889
1999-2000	1.037	1.265	1.026	1.011	1.312
2000-2001	1.024	1.024	1.020	1.004	1.048
2001-2002	0.987	1.221	0.996	0.991	1.205
2002-2003	0.983	1.153	0.986	0.997	1.133
2003-2004	1.014	1.004	1.004	1.009	1.018
2004-2005	0.998	1.024	1.001	0.997	1.022
2005-2006	1.008	0.980	0.995	1.013	0.989
2006-2007	1.019	0.911	1.019	1.000	0.928
Geometric mean	**1.001**	**1.020**	**1.001**	**1.000**	**1.021**
Cumulative 1997-2007	**1.010**	**1.219**	**1.010**	**1.000**	**1.231**

Note. (a) The table presents Malmquist indexes productivity changes. A bank's productivity change could be due to either a change in *technical efficiency* or by changes in *technology*, technological progress in the industry, or both. The *total factor productivity* change is the product of *technical efficiency* change and *technological* change. *Technical efficiency* change is decomposed in *pure technical efficiency change* and *scale efficiency change*. (b) The table highlights in bold the geometric mean as well as the compounded change for the period 1997-2007.

Table 7

Total Factor Productivity Change Direction and their Components (1997-2007)

Country	Technical efficiency change	Technological change	Pure technical efficiency change	Scale efficiency change	Total factor productivity change
Argentina	(–)	(+)	(–)	(–)	(+)
Brazil	(0)	(+)	(0)	(0)	(+)
Chile	(–)	(+)	(+)	(–)	(+)
Colombia	(–)	(+)	(–)	(–)	(+)
Ecuador	(0)	(+)	(+)	(–)	(+)
Mexico	(+)	(–)	(–)	(+)	(–)
Venezuela	(+)	(+)	(+)	(0)	(+)

Chile's total productivity change is 16.1% (an average of 1.5% per year). This change is due to the high technological progress during the period. The country shows a modest increase in pure technical efficiency and a small decrease in scale efficiency during the period, resulting in an inconsequential decline in efficiency. Colombia's total productivity change is 6.2% over the period. Similar to Chile, this increase in productivity is due to technological progress and a small decrease in technical efficiency.

Ecuador's total productivity increased 74.7% during the period. This change is attributed to consistent technological progress after the reforms of 2002 (14.0, 7.4, and 5.7% in 2003, 2004, and 2005, respectively). Moreover, inefficient banks have been able to catch up to efficient banks, as shown by the increase in technical efficiency. Thus, average banks have shown improvement in using resources during the period.

Mexico is the only country that shows a decline in total productivity (7.3%), basically due to the technological regression the country experienced during the sample period. Nevertheless, the country has seen an increase in technical efficiency, which is a consequence of scale inefficient banks moving toward better scales rather than improving the use of resources.

Venezuela had an increase in total productivity (23.1%) because of its technological progress. There is no substantial increase in technical and scale efficiency, meaning that inefficient banks have not been able to catch up with efficient ones during the period.

In summary, most of the countries have experienced technological progress in their banking industries without increasing technical efficiency. This technological progress may be associated with high investments in technology during periods of economic growth. It follows that the negative correlation between efficiency and economic growth found in fixed-effects regression analysis could be explained by the technological progress combined with the stagnation in technical efficiency (i.e., inefficient banks remain inefficient). More importantly, countries that experienced a banking crisis (Argentina, Colombia, Ecuador, and Venezuela) and made further reforms have not seen a substantial increase in technical efficiency (e.g., better use of resources and better scales), but an increase in their respective production frontiers.

Concluding Remarks

Employing DEA, we estimate and compare the efficiency and productivity of seven Latin American countries (Argentina, Brazil, Chile, Colombia, Ecuador, Mexico, and Venezuela). Consistent with the literature, we find that profit inefficiency is higher than cost inefficiency in our sample of Latin American banks, suggesting that most of the profit inefficiency is from the revenue side. Likewise, revenue efficiency is lower than cost efficiency in all countries, supporting the idea that profit inefficiency may be a consequence of revenue inefficiency. Further decomposition of revenue efficiency into revenue allocative efficiency and technical efficiency suggests that the source of inefficiency in the sample is regulatory (allocative) rather than managerial (technical). Thus, most Latin American countries confront either a regulatory framework that provides disincentives for economic efficiency or an unhealthy economic environment that forces managers to choose a suboptimal mix of inputs and banking services. In addition, the decomposition of technical efficiency into pure technical efficiency and scale efficiency suggests that inefficiency is the result of banks operating at a suboptimal scale rather than banks wasting resources.

Further study of the determinants of banking efficiency shows that *NIM* is negatively related to all measures of efficiency, with the exception of revenue allocative efficiency, which is consistent with the assertion that wider margins suggest lower competition (Demirgüç-Kunt & Levine, 1996). Moreover, the signs of association between efficiency measures and traditional measures of bank performance such as asset quality ratios (loan loss reserves over gross loans), capital ratios (equity over total assets), and operations ratios (*ROE*, *ROA*, and cost-to-income ratio) are consistent with what practitioners would expect: efficient banks have lower overhead costs relative to total income, use resources better, have higher quality portfolios, and have higher earnings (i.e., higher *ROA* and *ROE*) than inefficient ones.

Proxies for financial structure development show mixed results. For instance, concentration, measured as total assets of the three biggest banks over the country's total bank assets, is negatively related to efficiency, suggesting a degree of oligopoly in Latin America banking industries. Also, contrary to our hypothesis, economic efficiency (cost, revenue, profit) and allocative efficiency are negatively related to both credit provided by banks to the private sector and stocks traded as percentage of the GDP. The greater the stock market development, the lower is bank efficiency. The more credit the banking system provides to the private sector, the lower is bank efficiency. These results imply that Latin American banks tend to choose a suboptimal mix of output services.

Confirming previous findings for Latin American countries (Carvallo & Kasman, 2005), we find that Latin American countries with larger economies tend to have lower bank efficiency, as implied by the fact that GDP per capita is negatively related to efficiency. Moreover, higher inflation and higher real interest rates are shown to harm banking efficiency, whereas levels of savings in a country are positively related to revenue and allocative efficiency.

During the period 1997-2007, banks in our sample operated in a liberalized environment, and we find that most of the countries in our sample have had technological progress in their banking industries. However, with the exception of Ecuador, these banking industries have seen almost no increase in technical efficiency, implying that inefficient banks have not been able to catch up with efficient ones during the period. More importantly, countries that experienced a banking crisis during the period under study – and subsequently made further reforms to improve their banking systems – have not significantly increased their technical efficiency.

Endnotes

1 In a more global sense, the main objectives of financial liberalization were economic growth and stabilization of the economies. Unfortunately, as Stiglitz (2000) pointed out, the opposite was observed.

2 Charnes, Cooper, and Rhodes (1978) used the term DMU because DEA can be used not only to measure efficiency of firms but also branches within a firm. Our DMUs are banks.

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