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Bank efficiency in Latin America

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1.1 Introduction

Across Latin America, the period from the mid-1980s is characterised by fundamental shifts in public policy that have led to a reconfiguration of the industrial structure of national banking sectors. Policies associated with financial repression, namely interest rate controls and directed lending, were replaced by liberal policies that sought to increase competition and bank efficiency. Amendments to entry and exit conditions, the privatisation of state-owned banks and repeal of restrictions on foreign bank entry led to changes in bank ownership and the reform of governance (Carvalho, Paula and Williams, 2009). Improvements to bank governance that temper the risk-taking behaviour of bank owners are expected to lead to increases in bank efficiency (Caprio, Laeven and Levine, 2007; Laeven and Levine, 2009).

Latin America was badly affected by regional banking crises during the mid-1990s. The resolution of the crises required extensive government intervention that led to increases in market concentration (Domanski, 2005). Intervention involved a restructuring process that included the nationalisation of banks; transfer of ownership to healthy institutions; liquidation of bankrupts; and use of public funds to recapitalise and give liquidity to distressed banks. As a result, Latin American banking sectors operate under conditions of monopolistic competition (Gelos and Roldós, 2004). In terms of efficiency, increases in concentration may stifle competition because concentrated markets lack market discipline, which leads to lower efficiencies (Berger and Hannan, 1998). In spite of this concern, across the region there was an implicit assumption that private ownership would lead to a more efficient outcome, especially as public banks had served political and social purposes (Carvalho, Paula and Williams, 2009). Public ownership of banks is a feature of institutional and financial underdevelopment (La Porta et al., 2002), and the state's share of banking sector assets had been around 45% and 50% in Argentina and Brazil in the early 1990s (Carvalho, Paula and Williams, 2009). At this

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time, public ownership of banking sector assets amounted to 100% in Mexico following the 1982 nationalisation in response to the debt crisis (Haber, 2005). According to Ness (2000), public ownership created moral hazards between the government's economic and political goals and bank's business goals, and the relatively large size of public banks conferred a too-big-to-fail status that required frequent use of public funds to support ailing institutions.

To facilitate competition and improve efficiency, and to recapitalise distressed banks, governments repealed restrictions on foreign bank entry. The sale of local banks to foreigners is based on an assumption that private ownership is more effective in resolving agency problems (Megginson, 2005), and foreign banks possess superior management skills and technological capabilities that let them export efficiencies from home to host. Foreign bank entry is expected to boost banking sector efficiency because incumbent domestic banks must improve efficiencies or face losing market share. Operational diseconomies associated with distance from the home headquarters and cultural difference between the home and host countries can raise costs and lessen efficiencies at foreign banks (Berger et al., 2000; Mian, 2006). There is evidence to suggest foreign bank penetration in the post-restructuring period in Latin America did improve competition particularly when more efficient and less risky foreign banks entered the market (Jeon, Olivero and Wu, 2010). Efficiencies may be adversely impacted because foreign banks could 'cherry pick' the best customers and force local banks to service higher risk customers; foreign banks face information constraints and are less effective at monitoring soft information, which suggests credit to the private sector may be lower and certain sectors could face financial exclusion under conditions of increasing foreign bank penetration.

In order to investigate bank inefficiency in Latin America, we use a relatively new approach that deals with the problems associated with firm heterogeneity over time. Bank inefficiency is measured in terms of a bank's deviation from a best-practice frontier that represents the underlying production technology of a banking industry. Best-practice or efficient frontiers can be estimated by parametric and/or non-parametric methods. The most popular approaches are stochastic frontier analysis (Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977) and data envelopment analysis (Farrell, 1957; Banker, Charnes and Cooper, 1984). The results reported later in this chapter apply the former approach to estimate bank efficiency and utilise methodological advances in efficiency modelling to account for an anomaly that can 'seriously distort' estimated inefficiency (Greene, 2005a, 2005b; Bos et al., 2009). As just noted, the anomaly is how to treat cross-firm heterogeneity. Standard panel data approaches confound any time-invariant cross-firm heterogeneity with the inefficiency term. The problem may be resolved using so-called true effects models and random parameters models that are adapted to stochastic frontier analysis. This class of model is attractive because it relaxes the restrictive assumption of a common production technology across firms (Tsionas, 2002).

The remainder of this chapter outlines the bank efficiency literature on Latin America and then briefly presents our results on four systems – Argentina, Brazil, Chile and Mexico – from 1985 to 2010 using modelling approaches that deal with the problem of firm heterogeneity in panel estimations.

1.2 Privatization and foreign banks in Latin America

Bank privatisation and foreign bank penetration altered the market structure of national banking sectors and transformed the governance structure of banks as new, private owners (domestic and foreign) assumed control of banks. Formerly, Argentina and Brazil had extensive state-owned banking sectors, but privatisation offloaded banking sector assets onto the private sector that was expected to manage the assets more efficiently (Carvalho, Paula and Williams, 2009). State-owned banks had served political and social purposes but their characteristics included weak loan quality, underperformance, and poor cost control. Yet, privatisation outcomes are variable. In Argentina and Brazil, privatised bank performance improved post-privatisation (Berger et al., 2005; Nakane and Weintraub, 2005). In contrast, the failed 1991 Mexican bank privatisation programme cost an estimated $65 billion (Haber, 2005). Across the region, foreign banks have acquired large, local banks, many under temporary government control for restructuring. Some evidence finds a positive association between foreign bank penetration and bank efficiency. There are caveats: the need to distinguish between the performance of existing foreign banks and local banks acquired by foreign banks; and to disentangle the effects of foreign bank entry from other liberalisation effects that could impact bank efficiency.

Studies report differences in performance between local, private-owned and foreign-owned banks. Foreign banks achieved higher average loan growth (in Argentina and Chile) with loan growth stronger at existing foreign banks compared to acquired foreign banks. This suggests management at foreign bank acquisitions focused on restructuring their acquisitions and integrating operations with the parent (foreign) bank. The cautious nature of foreign bank strategies explains why foreign banks, and foreign bank acquisitions in particular, achieved better loan quality than local banks (Clarke, Crivelli and Cull, 2005), although stronger provisioning and higher loan recovery rates translated into weaker profitability at foreign banks. Foreign banks are relatively more liquid, rely less on deposit financing and produce stronger loan growth during episodes of financial distress than domestic banks. It is suggested that the greater intermediation efficiency of foreign banks arose because they were more able to evaluate credit risks and allocated resources at a faster pace than their local competitors (Crystal, Dages and Goldberg, 2002).

Evidence from Argentina shows state-owned banks underperformed against private-owned and foreign-owned banks due partly to poor loan quality associated with direct lending and subsidised credit. Bank privatisation produced efficiency gains because of falling non-performing loans and higher profit efficiencies. However, local M&A activity and foreign bank entry exerted little effect on bank performance (Berger et al., 2005). These findings do not generalize to Brazil where foreign banks faced difficulties in adapting to the peculiarities of the Brazilian banking sector, which is dominated by local, private-owned banks (Paula, 2002). The empirical record offers no support to suggest foreign banks are more or less efficient than domestic banks (Guimarães, 2002; Vasconcelos and Fucidji, 2002). This is unsurprising in the light of evidence that the operational characteristics and balance sheets of domestic and foreign banks are similar (Carvalho, 2002). Hence, the expected benefits of foreign bank penetration have been slow to emerge because foreign banks follow operational characteristics similar to large domestic, private-owned banks (Paula and Alves, 2007).

Although foreign bank penetration and foreign banks' share of bank lending are positively related, evidence suggests that foreign banks engage in cherry-picking behaviour. In Argentina and Mexico, foreign banks concentrated lending in the commercial loans market and limited exposure to the household and mortgage sectors (Dages, Goldberg and Kinney, 2000; Paula and Alves, 2007). Foreign bank acquisitions in Argentina used growth in lending to diversify away from manufacturing and target consumer markets. In addition, foreign banks aggressively penetrated regional markets that eliminated concerns over geographic concentration and increased regional lending to offset changes in local banks' lending. Lastly, foreign banks are an important source of finance. Their loan growth is higher (better quality and less volatile) than local (especially state-owned) banks (Dages, Goldberg and Kinney, 2000). Foreign banks – and private local banks – responded to market signals with pro-cyclical lending that is sensitive to movements in GDP and interest rates. Foreign banks' loan growth and lower volatility – even during crisis periods – suggests they can help to stabilise bank credit (Dages, Goldberg and Kinney, 2000).

Whereas policymakers expect consolidation to lead to greater competition and efficiency improvements, there is the possibility that competitive gains would not materialise, and instead bank market power would increase. The latter implies that the evolution of highly concentrated market structures could limit the deepening of financial intermediation and the development of more efficient banking sectors (Rojas Suarez, 2007). Since a non-competitive market structure often produces oligopolistic behaviour by banks, the suggestion is that more consolidation may incentivise banks to exploit market power rather than become more efficient. In general, the literature rejects the notion of collusion between banks, but evidence from Brazil suggests that banks possess some degree of market power (Nakane, Alencar and Kanczuk, 2006). Other Brazilian evidence illustrates the complexities associated with identifying competition effects: whilst the banking sector operates under monopolistic competition, this finding cannot be generalised across ownership and size.

1.3 Methodology

The stochastic frontier production function (see Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977) specifies a two-component error term that separates inefficiency and random error. In the composed error, a symmetric component captures random variation of the frontier across firms, statistical noise, measurement error and exogenous shocks beyond managerial control. The other component is a one-sided variable that measures inefficiency relative to the frontier. In its general form, the stochastic frontier cost function is written as

$$C_{it} = \left(\mathbf{X}_{it}\boldsymbol{\beta}\right)\cdot e^{v_{it}+u_{it}}; \quad i = 1,2,\ldots,N, \quad t = 1,2,\ldots,T, \tag{1.1}$$

where C_{it} is a scalar of the variable cost of bank i in period t; $\mathbf{X}_{it}$ is a vector of known inputs and outputs; $\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated; the v_{it} are independently and identically distributed $N\left(0,\sigma_v^2\right)$ random errors that are independently distributed of the u_{it}'s, which are non-negative random variables that account for the cost of inefficiency in production; the u_{it} are assumed to be positive and distributed normally with zero mean and variance σ_u^2.

The total variance is defined as $\sigma^2 = \sigma_v^2 + \sigma_u^2$. The contribution of the error term to the total variation is as follows: $\sigma_v^2 = \sigma^2 / (1+\lambda^2)$. The contribution of the inefficiency term is $\sigma_u^2 = \sigma^2\lambda^2 / (1+\lambda^2)$. Where σ_v^2 is the variance of the error term v, σ_u^2 is the variance of the inefficiency term u and λ is defined as σ_u/σ_v, providing an indication of the relative contribution of u and v to $\varepsilon = u + v$.

Estimation of Equation (1.1) yields the residual ε_{it}, meaning that the inefficiency term u_{it} must be calculated indirectly. The solution is proposed by Jondrow et al. (1982): the estimator uses the conditional expectation of u_{it}, conditioned on the realised value of the error term

$\varepsilon_{it} = (v_{it} + u_{it})$, as the estimator of u_{it}. In other words, $E|u_{it}/\varepsilon_{it}|$ is the mean inefficiency for the ith bank at time t. The Jondrow et al. (1982) estimator for panel data is shown in Equation (1.2):

$$E\left[u_{it}|\varepsilon_{it}\right] = \frac{\sigma\lambda\left(f\left(a_{it}\right)/\left[1-\Phi\left(a_{it}\right)\right]-a_{it}\right)}{1+\lambda^2}, \tag{1.2}$$

where $\sigma = \left(\sigma_v^2 + \sigma_u^2\right)^{1/2}$, $\lambda = \sigma_u/\sigma_v$, $\alpha_i = \pm\varepsilon_i\lambda/\sigma$, and $\phi(\cdot)$ and $\Phi(\cdot)$ are the density and distribution of the standard normal, respectively; $v_{it} \sim N\left(0,\sigma_v^2\right]$, $u_{it} = |U_{it}|, U_{it} \sim N\left[0,\sigma_{ui}^2\right]$ and ν_{it} is independent of u_{it}.

The availability of panel datasets boosted developments in the frontier literature. Early approaches modelled inefficiency as time invariant, a very restrictive assumption particularly in long datasets. Later panel data methods removed this limitation. Other challenges remained, including the key issue of how to treat observed and unobserved heterogeneity. Observed heterogeneity can be incorporated into the stochastic frontier cost function by specifying variables such as a time trend and/or other control factors. Their inclusion will affect measured inefficiency, however. Should the variables be specified as arguments in the cost function or as determinants of inefficiency in a second-stage analysis? Whilst arguments exist in both directions, ultimately, the decision is arbitrary.[1]

Unobserved heterogeneity presents more of a challenge. Generally, it enters the stochastic frontier through the form of either fixed or random effects. This approach can confound cross-firm heterogeneity with the inefficiency term that will bias estimated inefficiency. Greene (2005a) and Greene (2005b) solve this problem by extending both fixed effects and random effects models to account for unobserved heterogeneity. The literature refers to them as 'true' effects models.

The research strategy is to estimate alternative specifications of the stochastic frontier cost function in Equation (1.1). In the base case, we estimate a standard panel data cost function that assumes the inefficiency term follows a half-normal distribution with the following features: $U \sim N\left(0,\sigma_u^2\right)$ and $v \sim N\left(0,\sigma_v^2\right)$, where σ_v^2 is constant. This is Model 1. Model 2 is the true fixed effects model (Greene, 2005a, 2005b). An advantage of the effects models over the standard panel data approaches is that the former models relax the restrictive assumption of a common production technology across firms (Tsionas, 2002).

Models 3–6 belong to the random parameters class of models and the estimations we report are based on the general framework developed by Greene (2005a). In the most general cost function specification that is reported later, the coefficients on the linear terms in the output, input and time variables and the constant term are assumed to be random with heterogeneous means. The heterogeneous means of these random coefficients are linear in average asset size. The coefficients on the remaining cost function covariates (the control variables) are assumed to be constant. The log standard deviation of the half-normal distribution that is

[1] Alternative estimations approaches include those of Battese and Coelli (1995) (see for example, Pasiouras, Tanna, Zopounidis, 2009; and Lozano-Vivas and Pasiouras, 2010). The Battese and Coelli 1995 approach allows for estimation of inefficiency in a single step while controlling for country differences, and you can also include the same variables (if needed) in both the frontier function and the inefficient term without a problem. Another approach used to deal with cross-country frontier estimation is the use of the meta-frontier where individual country best-practice frontiers are enveloped by meta-frontiers and differences between country frontiers and the meta-frontier are gauged by technology gaps. See Bos and Schmiedel (2007) and Kontolaimou and Tsekouras (2010) for explanation of the meta-frontier approach.

used to define the inefficiency term in the cost function is assumed to be linear in asset size. The coefficient on asset size is assumed to be random with a constant mean. The most general specification is as follows:

$$
\begin{aligned}
&c_{it} = a_i + \boldsymbol{\beta}_i' \mathbf{x}_{it} + \boldsymbol{\phi}' \mathbf{y}_{it} + v_{it} + u_{it} \\
&v_{it} \sim N\left(0, \sigma_v^2\right), \quad \text{where} \quad \sigma_v^2 \text{ is constant} \\
&u_{it} = \left|U_{it}\right|, \quad \text{where} \quad U_{it} \sim N\left(0, \sigma_{ui}^2\right) \quad \text{and} \quad \sigma_{ui} = \sigma_u \exp(\theta_i) \\
&\left(\boldsymbol{\alpha}_i \boldsymbol{\beta}_i'\right) = (\overline{\boldsymbol{\alpha}}\overline{\boldsymbol{\beta}}')' + \Delta_{\alpha,\beta} s_i + \Gamma_{\alpha,\beta}(\mathbf{w}_{\alpha i} \mathbf{w}'_{\beta i})' \\
&\theta_i = \overline{\theta} + \delta_\theta s_i + \gamma_\theta w_{\theta i},
\end{aligned}
\tag{1.3}
$$

where $\mathbf{x}_{it}$ is a (27 × 1) vector of output, input and time variables; $\mathbf{y}_{it}$ is a (9 × 1) vector of other cost function covariates; and s_i is the average asset size of bank i. The coefficient vectors are as follows: $(\boldsymbol{\alpha}_i \boldsymbol{\beta}'_i)'$ is a (28 × 1) vector of random coefficients; $(\overline{\boldsymbol{\alpha}}\overline{\boldsymbol{\beta}}')'$ and $\boldsymbol{\Delta}_{\alpha,\beta}$ are (28 × 1) vectors of (fixed) coefficients; $\Gamma_{\alpha,\beta}$ is a free (4 × 4) lower-triangular matrix of (fixed) coefficients; $\boldsymbol{\phi}$ is a (9 × 1) vector of (fixed) coefficients; θ_i is a random coefficient; $\overline{\theta}$ and $\gamma\theta$ are (fixed) coefficients. $(\mathbf{w}_{\alpha i} \mathbf{w}'_{\beta i})'$ is a (28 × 1) vector of NIID random disturbances, where $w'_{\beta i} = \{w_{\beta ji}\}$ for $j = 1, \ldots, 27$; and $w\theta_i$ is a NIID random disturbance. The individual elements of the coefficient vectors are denoted as follows: $\beta'_i = \{\beta_{ji}\}$, $\overline{\beta}' = \left\{\overline{\beta}_j\right\}$ for $j = 1, \ldots, 3$; $\Delta_{\alpha,\beta'} = \left\{\delta_j\right\}$ for $j = 0, \ldots, 27$; $\phi' = \{\phi_j\}$ for $j = 1, \ldots, 9$; and $\Gamma_{\alpha,\beta} = \{\gamma_{jk}\}$ for $j = 0, \ldots, 27$ and $k = 0, \ldots, j$. The specification of $\Gamma_{\alpha,\beta}$ implies the variances of the random coefficients conditional on s_i are $\operatorname{var}\left(\alpha_i \middle| s_i\right) = \gamma_{00}^2 v$, $\operatorname{var}\left(\beta_{ji} \middle| s_i\right) = \sum_{k=0}^{i} \gamma_{jk}^2$, $\operatorname{var}\left(\theta_i \middle| s_i\right) = \gamma_\theta^2$. The corresponding conditional standard deviations are denoted as $\sigma(\alpha_i | s_i)$ and so on. The specification of $\Gamma_{\alpha,\beta}$ allows for non-zero conditional covariances between the elements of $(\alpha_i \beta'_i)'$.

We estimate various restricted versions of Equation (1.3). For a stochastic cost frontier with no random coefficients (Model 2), the parameter restrictions are: $\{\delta_j\} = 0$ for $j = 0, \ldots, 27$; $\{\gamma_{jk}\} = 0$ for $j = 0, \ldots, 27$, $k = 0, \ldots, j$; and $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$. For random (individual) effects with homogeneous means (Model 3), the restrictions are: $\{\delta_j\} = 0$ for $j = 0, \ldots, 27$; $\{\gamma_{jk}\} = 0$ for $j = 1, \ldots, 27$, $k = 0, \ldots, j$; and $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$. For random effects and random coefficients on the output, input and time variables with homogeneous means (Model 4), the restrictions are: $\{\delta_j\} = 0$ for $j = 0, \ldots, 27$; and $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$. For random effects and random coefficients on the 28 output, input and time variables with heterogeneous means (Model 5), the restrictions are $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$. For random effects and random coefficients on the 28 output, input and time variables with homogeneous means, and a random coefficient with a heterogeneous mean in the equation for the log standard deviation of the half-normal distribution used to define the inefficiency term (Model 6), the restrictions are $\{\delta_j\} = 0$ for $j = 0, \ldots, 28$. The heterogeneous means of the random coefficients in Models 5 and 6 are linear in average asset size.

The random coefficient stochastic frontier cost function is estimated by maximum simulated likelihood. In the estimation procedure, we use 500 Halton draws to speed up estimation and achieve a satisfactory approximation to the true likelihood function. u_{it} has a half-normal distribution truncated at zero to signify that each bank's cost lies either on or above the cost frontier, and deviations from the frontier are interpreted as evidence of the quality of bank management. The choice of distribution for the inefficiency term is arbitrary and other distributions are employed elsewhere (Greene, 2008). Efficiency analysis is characterised by arbitrary assumptions, and it is not always possible to carry out formal statistical tests between alternatives; for instance, the random coefficient models we estimate are not nested.

1.4 Model specification and data

We model the bank production process using the intermediation approach that assumes banks purchase funds from lenders and transform liabilities into the earning assets demanded by borrowers (Sealey and Lindley, 1977). The underlying cost structure of the banking sector is represented by the translog functional form. A unique feature of this study is the construction of a panel dataset covering over a quarter of a century from 1985 to 2010 for banks from Argentina, Brazil, Chile and Mexico. Financial statements data is sourced from the IBCA and BankScope databases. Data is deflated by national GDP deflators and converted in US$ millions at 2000 prices. The dimension of the dataset is 419 banks and 4571 observations over 26 years. Bank ownership is identified using BankScope, central bank reports, academic papers, newswire services, and bank websites. The macroeconomic data is from the World Bank Financial Indicators and World Economic Outlook databases. Table 1.1 shows the descriptive statistics of the sample banks.

Table 1.1 Descriptive statistics for the stochastic frontier cost function.

Variables[a]	Mean	Std. dev.	Minimum	Maximum
Variable cost ($m)	773.3	2 433.8	0.07	59 790.1
Loans ($m)	1963.9	5 517.8	0.04	83 773.5
Customer deposits ($m)	1943.1	5 655.3	0.02	83 653.6
Other earning assets ($m)	1748.8	5 817.4	0.00	85 888.7
Total assets ($m)	4425.0	13 446.2	2.76	204 730.0
Price of financial capital	0.1777	0.2030	0.0014	1.0789
Price of physical capital	0.8205	0.7816	0.0309	5.0234
Price of labour	0.0304	0.0233	0.0005	0.1222
Equity-to-assets[b]	0.0943	0.0214	0.0333	0.2330
Z score (rolling four years)[b]	20.028	12.742	3.280	81.144
Herfindahl index	1144.8	770.0	584.3	7591.4
Loan loss reserves-to-loans[b]	0.1263	0.0938	0.0113	0.3628
Diversification index[b,c]	0.3554	0.0748	0.1151	0.4716
GDP per capita ($m)	5228.1	2 211.9	2606.4	10 418.1
GDP growth	0.0333	0.0400	−0.1089	0.1228
CR – bank credit-to-GDP	0.6303	0.3285	0.2248	2.1292
SO – state-owned assets/ total assets	0.1363	0.3431	0.0000	1.0000

[a]The data is expressed as ratios unless otherwise indicated.
[b]The data is weighted annual averages where the weight is the share of bank i in total assets in country j at time t.
[c]The diversification index is calculated for bank income as in Sanya and Wolfe (2011).

We employ stochastic frontier cost function and translog functional form methodologies to estimate cost inefficiency. The cost function specifies three outputs in value terms (loans, deposits and other earning assets) and three inputs expressed as prices (the prices of financial capital, physical capital and labour). The specification of customer deposits as an output is a contentious issue in the literature. We take the view that customers purchase deposit accounts for the services that they offer, such as cheque clearing, record keeping and safe keeping. Customers do not pay for these services explicitly and banks must incur implicit costs, such as labour and fixed capital costs, in the absence of a direct revenue stream. Fixler and Zieschang (1992, p. 223) suggest banks cover these costs by setting lending rates in excess of deposit rates and propose that 'deposits … are simultaneously an input into the loan process and an output, in the sense that they are purchased as a final product providing financial services'. Berger and Humphrey (1992) treat deposits as an output because of the large share of bank added value that they generate.

The cost function by construction assumes a common production technology across banks. This assumption is unrealistic given the rate of technological progress over such a long time period. Our cost function is common to banks from four countries and we should account for the effect of cross-country differences as well as inter-temporal differences on bank cost. We control for inter-temporal variation in cost by specifying a time trend, its quadratic term (T^2) and interaction terms between time and outputs, and time and inputs. The sum of the estimated coefficients on the time variables measures the effect of technical change in production on bank cost.[2] We control for the impact of cross-country differences on bank cost by specifying a vector of banking sector and economic variables at country level.

To mitigate potential endogeneity issues, we construct weighted annual averages of four banking sector variables to proxy for underlying conditions, where the weight is the share of bank i in total assets in country j at time t. The variables are as follows:

- The ratio of equity-to-assets (ETA) or capitalisation that is positively associated with prudence or risk aversion. We expect capitalisation is positively related to stability because better capitalized banks are less susceptible to losses arising from unanticipated shocks.
- The Z score (Z) is constructed for each bank as $Z = \text{RoA} + \text{ETA}/\sigma_{\text{RoA}}$ which combines a performance measure (RoA, return on assets), a volatility measure to capture risk (σ_{RoA}) over a four-year rolling window and book capital (ETA, equity-to-assets) as a proxy for soundness or prudence of bank management. Z is expressed in units of standard deviation of RoA and shows the extent to which earnings can be depleted until the bank has insufficient equity to absorb further losses. Lower values of Z imply a greater probability of bankruptcy with larger values implying stability. Our measure of Z is the natural logarithm of Z plus 100.
- It is common to control for differences in the risk appetite of management across banks by specifying variables like the stock of loan loss reserves (LLR)-to-gross loans to proxy asset quality. However, this variable is not strictly exogenous if managers are inefficient at portfolio management or skimp on controlling costs. Hence, we use the

[2] An alternative approach specifies fixed time effects using dummy variables to control for the impact of changes in bank regulations and other government policies upon bank cost.

weighted annual average to proxy the underlying level of risk facing the banking sector (Berger and Mester, 1997).

- We measure income diversification (DIV) using a Herfindahl type index that is calculated as $\sum_{i=1}^{n}\left(X_i / Q\right)^2$ where the X variables are net interest revenue and net non-interest income and Q is the sum of X (Acharya, Hasan and Saunders, 2006). Income diversification is proxy for a bank's business model (Fiordelisi, Marques-Ibanez and Molyneux, 2011). The literature focuses on establishing the benefits of diversification in terms of reducing the potential for systemic risk (Demsetz and Strahan, 1997), though the empirical evidence on this point is mixed (Stiroh and Rumble, 2006). The expected relationship between diversification and bank cost is less clear cut although some studies find an inverse link.
- The Herfindahl–Hirschman index of assets concentration in each country by year is specified to control for the effects of increases in market concentration on bank cost. Under the franchise value hypothesis, there is less incentive for banks to assume unnecessary risks in more concentrated markets.
- The natural logarithm of GDP per capita is a proxy for country-level wealth effects.
- We capture business cycle effects by the annual growth in GDP (GDPCHA).
- The ratio of banking sector credit-to-GDP indicates financial deepening, which Levine (2005) suggests is important in exerting corporate governance on bank borrowers. Incremental credit provision requires further screening and monitoring costs for banks that could reduce cost efficiencies.
- The ratio of state-owned bank assets-to-banking sector assets in country j at time t is proxy for the level of financial repression. State-ownership is reported to result in poorly developed banks (Barth, Caprio and Levine, 2001) and less cost efficient banks (Megginson, 2005). State-owned banks may face a soft budget constraint, which implies that incentives for managers to behave in a cost-minimising manner are absent (Altunbas, Evans and Molyneux, 2001). Hence, the underperformance of state-owned banks is correlated with the level of government involvement and the perverse incentives of political bureaucrats (Cornett et al., 2010).

The stochastic frontier cost function is written in Equation (1.4) as

$$\begin{aligned}\ln\left(\frac{VC}{P_3}\right) &= (\alpha + w_i) + \sum_{i=l}^{3}\beta_i \ln\left(Q_i\right) + \sum_{k=l}^{3}\varphi_l \ln\left(\frac{P_k}{P_3}\right) \\ &+ \frac{1}{2}\left[\sum_{i=1}^{3}\sum_{j=1}^{3}\theta_{ij}\ln\left(Q_i\right)\ln\left(Q_j\right) + \sum_{k=1}^{3}\sum_{l=1}^{3}\varphi_{kl}\ln\left(P_k\right)\ln\left(P_l\right)\right] + \sum_{ik=1}^{3}\Omega_{ik}\ln\left(Q_i\right)\ln\left(\frac{P_k}{P_3}\right) \\ &+ \kappa_t T + \frac{1}{2}\kappa_{tt}T^2 + \sum_{i=1}^{3}\rho_{ti}\ln\left(Q_i\right)*T + \sum_{k=1}^{3}\varsigma_{tk}\ln\left(P_k\right)*T + \eta_k\sum_{k=1}^{9}\text{controls}_{kt} + \ln\varepsilon_c + \ln\mu_c,\end{aligned} \tag{1.4}$$

where

$\ln(VC/P_3)$ is the natural logarithm of variable cost (the sum of interest paid, personnel expense and non-interest expense) normalised by P_3;

ln Q_i is the natural logarithm of i output values (loans, deposits and other earning assets);

ln P_k is the natural logarithm of k input prices (P_1 is the price of financial capital, that is the ratio of interest paid-to-purchased funds; P_2 is the price of physical capital, that is the ratio of non-interest expenses-to-fixed assets; and P_3 is the price of labour, that is the ratio of personnel expense-to-total assets); and

T is a time trend where 1985 is equal to 1…2010 is equal to 26.

Controls comprise a vector of the following variables:

ETA is the weighted annual average of the ratio of equity-to-assets to proxy capitalisation.

Z is the weighted annual average of the Z score expressed as the log of $Z4$ plus 100.

HHI is the natural logarithm of the Herfindahl–Hirschman index of total assets.

LLR is the weighted annual average of the ratio of loan loss reserves-to-gross loans.

DIV is the weighted annual average of the diversification index.

GDP is the natural logarithm of real gross domestic product per capita.

GDPCHA is the rate of annual GDP growth.

CR is the ratio of bank credit to the private sector-to-GDP.

SO is the ratio of state-owned bank assets-to-banking sector assets.

ε_i are identical and independently distributed random variables, which are independent of the μ_i, which are non-negative random variables that are assumed to account for inefficiency.

α, β, ψ, θ, ϕ, Ω, κ, ρ, ς and η are the parameters to be estimated using maximum likelihood methods.

Standard restrictions of linear homogeneity in input prices and symmetry of the second-order parameters are imposed on the cost function. Whilst the cost function must be non-increasing and convex with regard to the level of fixed input and non-decreasing and concave with regard to prices of the variable inputs, these conditions are not imposed, but may be inspected to determine whether the cost function is well-behaved at each point within a given dataset.

1.5 Estimated parameters and cost efficiency

We begin by considering the estimated coefficients of the stochastic frontier cost functions. In line with expectations, the coefficients on the output and input terms are significantly positive across the different specifications. In the standard panel data model, estimations of the inefficiency term are much larger compared with estimates obtained from 'true' random effects and random parameter models, which suggests that the standard model confounds heterogeneity and inefficiency. For example, in the true random effects and random parameter models, σ_u is more than half the size of the corresponding estimate in the standard model. This key finding, here, therefore suggests that failing to take account of firm heterogeneity results in efficiency underestimation – it also suggest that virtually all the previous evidence on bank efficiency is biased.

The dispersion in mean cost inefficiency that is reported in the literature suggests that different estimation techniques – samples and time periods – have an important bearing on measured inefficiency (Bauer et al., 1998). The distributional properties of the estimated cost efficiencies from each model are shown in Table 1.2. The mean cost efficiency for the true

Table 1.2 Descriptive statistics: variable cost efficiency by model (U_{it} = half-normal distribution).

Model number and type	Mean	Std. dev.	Minimum	Maximum	Skewness	Kurtosis
(1) Standard panel (SP) data model	0.7441	0.1172	0.4108	0.9760	–0.936	3.756
(2) True fixed effects	0.5577	0.0928	0.0579	0.9412	–1.046	6.719
(3) True random effects	0.8696	0.0395	0.3734	0.9776	–4.094	34.783
(4) Random parameters	0.8526	0.0627	0.2137	0.9802	–3.668	25.726
(5) RP heterogeneity in means of RPs	0.8547	0.0611	0.2344	0.9805	–3.510	25.200
(6) RP heterogeneity in variance of U_{it}	0.8300	0.0802	0.2281	0.9860	–1.950	9.690

RP refers to random parameter models.

Table 1.3 Spearman rank-order correlations of variable cost efficiency.

Model number and type	(1) Standard panel	(2) Fixed effects	(3) Random effects	(4) Random parameters	(5) RPM heterogeneity 1
(1) Standard panel					
(2) Fixed effects	0.6400				
(3) Random effects	0.6891	0.8150			
(4) Random parameters	0.5626	0.6772	0.7984		
(5) RPM heterogeneity 1	0.5531	0.6593	0.7862	0.8299	
(6) RPM heterogeneity 2	0.8262	0.4917	0.5793	0.4801	0.4777

(1) All coefficients are significant at the 1% level.

random effects and random parameter models ranges from 83% to 87%. The mean cost efficiency drawn from the standard model is just over 74% and its standard deviation is up to two times larger than the comparative figures for the random parameter models. The 'true' fixed effects model yields the lowest mean cost efficiency at less than 56%, and though standard deviation is less than the standard model, it is larger than in the random parameter models.

Bauer et al. (1998) suggest that measured efficiencies derived from alternative approaches should comply with a set of consistency conditions, such as efficiency should have comparable means, standard deviations and other distributional properties, and the different approaches should rank the banks in approximately the same order. Spearman rank-order correlation coefficients test the null of independence between two sets of rank efficiencies. After ranking cost efficiencies, we calculate the Spearman correlation coefficients for each pair of ranks and present the results in Table 1.3. The random parameter models produce the highest rank-order correlations. The highest correlations are between the 'true' random effects and random parameter models. Whereas each correlation coefficient is statistically significant at the 1% level, Table 1.3 demonstrates the variation in the size of the coefficients.

In this section, we report cost efficiency estimates drawn from the random parameters model that allows for heterogeneity to enter the means of the random parameters. We convert

Table 1.4 Rank cost efficiency by country, 1985–2010.

Year	Argentina	Brazil	Chile	Mexico	Year	Argentina	Brazil	Chile	Mexico
1985	0.2645	0.3701	0.3882	0.7882	1998	0.5117	0.5101	0.4617	0.4306
1986	0.9446	0.5779	0.5367	0.5595	1999	0.5194	0.4930	0.6295	0.3222
1987	0.8099	0.2956	0.4570	0.2891	2000	0.4235	0.5235	0.6330	0.3829
1988	0.1469	0.5028	0.7632	0.4013	2001	0.6451	0.5198	0.4653	0.3845
1989	0.0981	0.3199	0.5471	0.5582	2002	0.6596	0.4963	0.5898	0.5169
1990	0.0547	0.6525	0.5570	0.7015	2003	0.5771	0.5403	0.5556	0.6067
1991	0.8096	0.6006	0.6585	0.6434	2004	0.5663	0.4860	0.5717	0.5678
1992	0.6358	0.4812	0.5594	0.5860	2005	0.5988	0.5127	0.5261	0.5447
1993	0.5292	0.5012	0.5180	0.5556	2006	0.4803	0.4573	0.4520	0.5055
1994	0.4280	0.5548	0.4417	0.5567	2007	0.4420	0.4678	0.4985	0.4294
1995	0.6038	0.4346	0.4042	0.5549	2008	0.3728	0.4008	0.5367	0.2468
1996	0.5525	0.4118	0.3585	0.4613	2009	0.4111	0.5703	0.5483	0.4683
1997	0.4738	0.3983	0.3744	0.5326	2010	0.3941	0.5711	0.4866	0.6688

the cost efficiencies into average rank-order efficiencies following Berger, Hasan and Klapper (2004). The rank efficiencies are interpreted as follows. In Table 1.3, the average rank cost efficiency of Argentine banks is 0.2645 in 1985. It means that the average Argentine bank is more cost efficient than 26% of banks operating in Latin American over 1985–2010. As a test of robustness, we calculated rank cost efficiency at country level and correlated the ranks with the regional ranking. The correlation coefficient exceeds 0.9.

Table 1.4 shows average rank-order cost efficiency by country and year. The period from the mid-1980s to the early 1990s reveals a greater variation in mean cost efficiency, which is to be expected given the ongoing troubles associated with the international debt crisis. Nevertheless, if we compute average rank cost efficiency for 1985–1993, the value for each country is greater than the comparative data for 1994–2000 that covers the period of regional banking crises. For instance, for Mexico the averages are 0.5814 and 0.4573, respectively. We compute average rank cost efficiency for 2001–2006 and 2007–2010 to disentangle the impact of the global banking crisis upon regional cost efficiency. Average rank cost efficiency improves in each country between 1994–2000 and 2001–2006. The biggest improvement is in Argentina from 0.5042 to 0.5900, which made the average Argentine bank more cost efficient than 59% of Latin American banks during this period. However, the impact of the global crisis sees average rank cost efficiency decrease by around 31% in Argentina and 20% in Mexico (from 0.5900 to 0.4065, and 0.5177 to 0.4130, respectively). On the contrary, average rank cost efficiencies held up relatively well in Brazil and Chile with only minor reductions in comparison to the previous period: for Brazil, the mean rank cost efficiency equals 0.4909 in 2007–2010 and it is 0.5180 in Chile.

In Table 1.5 and Table 1.6, we present the average rank cost efficiencies by bank ownership in each country and by year. Table 1.5 shows private-owned domestic banks as well as state banks, and Table 1.6 shows the efficiency performance of foreign-owned banks divided into *de novo* entrants and entry made via mergers and acquisitions (M&A), respectively. Using the same sub-period classification to discuss the results, the average rank cost efficiency of state-owned banks fell between 1985–1993 and 1994–2000 (except in Chile) from 0.5332 to 0.4988 in Argentina, from 0.5245 to 0.4597 in Brazil and 0.6068 to 0.5224 in Mexico. Whilst this feature is unsurprising given the incidence of banking sector crises over

Table 1.5 Rank cost efficiency by country, 1985–2010 – state- and private-owned banks.

Year	Argentina	Brazil	Chile	Mexico	Year	Argentina	Brazil	Chile	Mexico
State-owned banks									
1985	0.8333	0.2381	0.2213	0.7882	1998	0.5828	0.4492	0.7103	—
1986	0.7318	0.5655	0.3470	0.5595	1999	0.4990	0.6515	0.7502	0.4631
1987	0.8077	0.2908	0.3758	0.2891	2000	0.3919	0.6443	0.7696	0.3916
1988	0.5049	0.6411	0.4844	0.4013	2001	0.5493	0.5981	0.6841	0.9005
1989	0.4771	0.3404	0.8289	0.6054	2002	0.5618	0.4460	0.8606	0.2590
1990	0.5896	0.7516	0.6655	0.7154	2003	0.6143	0.5673	0.6515	0.6165
1991	0.6248	0.5530	0.6471	0.7329	2004	0.4984	0.6391	0.5649	—
1992	0.5043	0.6114	0.7206	0.7633	2005	0.5866	0.6218	0.4603	—
1993	0.4871	0.4611	0.7852	0.6488	2006	0.4771	0.5259	0.2660	0.3540
1994	0.4444	0.4844	0.7311	0.7970	2007	0.4659	0.4815	0.1483	—
1995	0.5277	0.4425	0.6257	0.4868	2008	0.4597	0.5147	0.1755	0.6213
1996	0.5170	0.3700	0.4975	0.1989	2009	0.4901	0.6482	0.3448	0.4756
1997	0.3796	0.3349	0.5749	—	2010	0.4311	0.6207	0.2964	—
Private-owned banks									
1985	0.1507	0.4237	0.5218	—	1998	0.4879	0.5178	0.3860	0.3634
1986	0.9750	0.5802	0.5604	—	1999	0.4926	0.4697	0.7010	0.2391
1987	0.8101	0.3015	0.4672	—	2000	0.4220	0.5236	0.6327	0.3521
1988	0.0447	0.4019	0.7589	—	2001	0.6834	0.4570	0.5314	0.4199
1989	0.0666	0.2622	0.6208	0.3008	2002	0.7781	0.4949	0.5893	0.6111
1990	0.0190	0.6174	0.5976	0.2689	2003	0.5711	0.5639	0.5511	0.6610
1991	0.8482	0.6333	0.6428	0.6217	2004	0.5771	0.4963	0.4932	0.5847
1992	0.6768	0.4269	0.4991	0.6062	2005	0.5976	0.4782	0.5376	0.5862
1993	0.5300	0.5526	0.5043	0.5622	2006	0.4425	0.4574	0.4381	0.5243
1994	0.4510	0.5756	0.3633	0.5241	2007	0.3977	0.4536	0.4068	0.4063
1995	0.6530	0.4578	0.3857	0.4291	2008	0.3308	0.3673	0.6744	0.2382
1996	0.5619	0.4208	0.3178	0.4088	2009	0.3501	0.5281	0.6360	0.4449
1997	0.4864	0.4450	0.4220	0.4536	2010	0.3770	0.5632	0.5495	0.5471

1994–2000, we find that this pattern of performance is not common to private-owned banks in Argentina and Brazil for whom average rank cost efficiency is relatively stable at around 0.51 and 0.48 in each sub-period. In contrast, the reduction in average rank cost efficiency for private-owned banks in Mexico deteriorated by 31% compared to 14% for state-owned banks. In Mexico, the cost efficiency performance of banks remains relatively constant in the two subsequent sub-periods. In Brazil, rank cost efficiency improves for state-owned banks over 2001–2006 and it remains relatively constant during the 2007–2010 sub-period at 0.5607. Whereas state-owned bank efficiency performance in Argentina improves over 2001–2006 (to 0.5491), it deteriorates by 15% to 0.4662 in 2007–2010. Across the region, the cost efficiency performance of private-owned improves between 1994–2000 and 2001–2006: in ascending order, by 41% in Mexico, 18% in Argentina, 15% in Chile and less than 2% in Brazil. Only in Chile did private-owned banks improve cost efficiency performance over 2007–2010 (by 8%); cost efficiency deteriorated mildly in Brazil (by 6%) and substantially in Argentina and Mexico (by 40% and 33%).

Table 1.6 Rank cost efficiency by country; 1985–2010 – foreign-owned banks (*de novo* entry and via acquisition).

Year	Argentina	Brazil	Chile	Mexico	Year	Argentina	Brazil	Chile	Mexico
Foreign-owned banks (*de novo* entry)									
1985	—	0.2553	—	—	1998	0.5265	0.4580	0.4972	0.5430
1986	—	0.5977	—	—	1999	0.5223	0.4850	0.5351	0.4522
1987	—	0.2387	—	—	2000	0.3996	0.5045	0.7280	0.5042
1988	—	0.6474	0.8403	—	2001	0.6254	0.6738	0.3243	0.3454
1989	—	0.4870	0.3649	0.0120	2002	0.5989	0.5655	0.5581	0.4199
1990	—	0.6665	0.4546	0.8963	2003	0.5265	0.4845	0.5522	0.3622
1991	0.3292	0.5385	0.6320	0.0333	2004	0.6097	0.3860	0.6341	0.4408
1992	0.3250	0.5149	0.6816	0.0654	2005	0.5986	0.5374	0.4398	0.4180
1993	0.5677	0.3892	0.5361	0.2507	2006	0.5628	0.3880	0.4298	0.4189
1994	0.3642	0.5575	0.4818	0.7937	2007	0.5274	0.4326	0.6829	0.3290
1995	0.5862	0.3588	0.4187	0.8270	2008	0.4094	0.4363	0.3467	0.2504
1996	0.5493	0.4146	0.4074	0.5488	2009	0.4616	0.6333	0.4824	0.4097
1997	0.4925	0.3297	0.3384	0.6474	2010	0.3551	0.6154	0.4938	0.6681
Foreign-owned banks (acquisitions)									
1985	—	—	—	—	1998	0.5042	0.6542	0.4773	0.0807
1986	—	—	—	—	1999	0.6133	0.4972	0.6701	0.0665
1987	—	—	—	—	2000	0.5157	0.4885	0.4356	0.1255
1988	—	—	0.9438	—	2001	0.6634	0.3824	0.5150	0.2935
1989	—	—	0.2186	—	2002	0.5275	0.4233	0.5790	0.4896
1990	—	—	0.4332	—	2003	0.6965	0.5070	0.5509	0.7917
1991	—	—	0.8325	—	2004	0.5452	0.4715	0.6646	0.6661
1992	—	—	0.5658	—	2005	0.6435	0.5187	0.6861	0.5817
1993	—	—	0.4004	—	2006	0.4552	0.5396	0.5776	0.5941
1994	—	—	0.4472	—	2007	0.3975	0.6099	0.4792	0.6079
1995	—	—	0.3241	0.2719	2008	0.2973	0.3870	0.5805	0.2024
1996	—	—	0.2196	0.5110	2009	0.4198	0.5402	0.4927	0.5629
1997	0.4784	0.3312	0.3009	0.4229	2010	0.4416	0.4835	0.4190	0.8216

Table 1.6 shows the average rank cost efficiency of foreign-owned banks segmented by entry status, that is, *de novo* entrants and entrants through M&A mainly following the bank restructuring programmes of the mid-1990s. Some patterns of performance we describe earlier for state and private-owned banks are visible for *de novo* entrants; namely, the deterioration in performance between 1985–1993 and 1994–2000 (except Mexico). In Argentina, Brazil and Chile, average cost efficiency improves in 2001–2006 and remains relatively stable over 2007–2010 in Brazil and Chile, whereas it deteriorates by 22% in Argentina. In each country, except Mexico, the average *de novo* foreign entrant is more cost efficient than the average M&A entrant.

Foreign acquisitions of local banks take off over 1994–2000. Comparing the average rank cost efficiency of this cohort for 1994–2000 and 2001–2006 we observe improvements in performance in Argentina (by 10%), Chile (by 37%) and Mexico (by 185%), whilst a decline occurs in Brazil (by 11%). It is interesting to consider if foreign-acquired banks' cost efficiency performance held up during the 2007–2010 sub-period. Only in Brazil did foreign-acquired banks improve average rank cost efficiency (by 9%): performance falls of the magnitude of 36%, 17% and 9% are recorded in Argentina, Chile and Mexico, respectively.

1.6 Conclusion

This chapter contributes to the bank efficiency literature through its application of recently developed effects models for stochastic frontier analysis. We estimate several variants of this class of model including fixed and random effects models, and alternative specifications of random parameters models that accommodate heterogeneity in different ways. We find that estimated mean efficiency drawn from the effects models is greater and arguably more precise because heterogeneity is not confounded with inefficiency. Or to put another way, previous studies on bank cost efficiency provide underestimates of the 'true' efficiency of banking markets if they have used panel data and not controlled for firm heterogeneity.

We then chose one of these random effects and parameters model to analyse the evolution of average rank cost efficiency for Latin American banks between 1985 and 2010 and show the results by country, year and bank ownership. Here we find that bank cost efficiency generally deteriorated between 1985–1993 and 1994–2000 and this was particularly pronounced for state-owned institutions. The period up to 2006 experienced widespread foreign bank expansion in the region, reflecting a strengthened economic operating environment with cost efficiency generally improving over this period (even for state-owned Brazilian and Argentine banks). Since the 2007 crisis, cost efficiency appears to have either stabilised (foreign-owned banks) or mildly fallen (private banks). An interesting feature of our findings is that *de novo* foreign bank entry appears to be more cost efficient compared to entry via M&A.

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