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DEALING WITH CROSS-FIRM HETEROGENEITY IN BANK EFFICIENCY ESTIMATES: SOME EVIDENCE FROM LATIN AMERICA

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Abstract

This paper contributes to the bank efficiency literature through an application of recently developed random parameters models for stochastic frontier analysis. We estimate standard fixed and random effects models, and alternative specifications of random parameters models that accommodate cross-sectional parameter heterogeneity. A Monte Carlo simulations exercise is used to investigate the implications for the accuracy of the estimated inefficiency scores of estimation using either an under-parameterized, over-parameterized or correctly specified cost function. On average, the estimated mean efficiencies obtained from random parameters models tend to be higher than those obtained using fixed or random effects, because random parameters models do not confound parameter heterogeneity with inefficiency. Using a random parameters model, we analyse the evolution of the average rank cost efficiency for Latin American banks between 1985 and 2010. Cost efficiency deteriorated during the 1990s, particularly for state-owned banks, before improving during the 2000s but prior to the subprime crisis. The effects of the latter varied between countries and bank ownership types.

Keywords: Efficiency; stochastic frontier; random parameters models; bank ownership; Latin America

JEL classification: C23; D24; G21

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1. Introduction

Bank inefficiency is measured in terms of a bank's deviation from a best practice frontier that represents the industry's underlying production technology. Best practice or efficient frontiers can be estimated by parametric and/or non-parametric methods. The most popular approaches are stochastic frontier analysis (Aigner et al, 1977; Meeusen and van den Broeck, 1977), and data envelopment analysis (Farrell, 1957; Banker et al., 1984). In this paper, we apply the former approach to estimate bank efficiency, and utilizing methodological advances in efficiency modelling to account for an anomaly that can "seriously distort" estimated inefficiency (Greene, 2005a, p. 270, 2005b; Mester, 1997; Orea and Kumbhakar, 2004; Bos et al., 2009). The anomaly is cross-firm heterogeneity in the parameters of the cost function. Standard panel models confound any time invariant cross-firm heterogeneity with the inefficiency term. The problem may be resolved using 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).

There are few applications of non-standard stochastic frontier models for panel data in the bank efficiency literature. Greene (2005a) estimates a stochastic frontier cost function with fixed effects and random effects for a sample of 500 US banks, and draws comparisons with other panel data models commonly used in the efficiency literature. Greene (2005b) reports results obtained using two random parameters specifications. The results indicate that model specification impacts the precision of estimated inefficiencies. This is a crucial point, because estimated inefficiency is often used as a dependent variable in second-stage regression for the determinants of efficiency. Bos et al. (2009) report that the efficiency rankings of German savings banks are sensitive to the treatment of heterogeneity. Tecles and Tabak (2010) use a Bayesian stochastic frontier to estimate cost and profit efficiency for a sample of Brazilian banks between 2000 and 2007, noting the need to compare their estimated efficiencies with those drawn from random effects models to combat heterogeneity issues. Sun and Chang (2011) use a heteroskedastic stochastic frontier model to estimate the cost efficiency of a sample of Asian banks. The novelty in their approach is that the posited determinants of inefficiency affect the latter in a non-monotonic manner. In an application to Mexican banks, Barros and Williams (2013) estimate three random parameters stochastic frontier models. Mean cost efficiency is shown to be higher than that obtained from standard panel data estimates.

The first objective of this paper is to example whether random parameters models suitably disentangle heterogeneity and inefficiency, thereby yielding more precise estimates of inefficiency. As a baseline, we estimate a standard stochastic cost frontier, before employing fixed effects and random effects specifications to estimate inefficiency. We then control for cross-sectional heterogeneity in the parameters of the cost function, by estimating several random parameters specifications. To assess the implications of the choice between the random effects and random parameters specifications, we report results from a Monte Carlo simulation exercise to compare the true and estimated inefficiency scores when the model specification corresponds to the true data generating process for the cost function, and when the estimated model differs from the true data generating process. For our data sample, we compare estimated parameters across models including variance parameters, the distribution of the inefficiency scores, and rank order correlations to examine how different approaches to dealing with bank heterogeneity affect the estimated cost inefficiencies. Our principal methodological conclusion is that efficiency appears to be underestimated if firm heterogeneity is confounded with inefficiency in the model specification. This suggests that much of the previous literature understates the “true” level of bank efficiency.

A second objective of the paper is to investigate the evolution of bank cost efficiency over the last quarter of a century in four Latin American countries: Argentina, Brazil, Chile and Mexico. Over this period, there have been several fundamental shifts in public policy, which have contributed to a reconfiguration of the industrial structure of the banking sectors of the major Latin American countries. A regulatory regime often characterized as financial repression, which included measures such as interest rate controls and directed lending, has been replaced by liberal policies that seek to promote competition and improve efficiency. Measures such as the privatization of state-owned banks, and the removal of restrictions on foreign bank entry, have contributed to changes in ownership structure and the reform of governance (Carvalho et al., 2009). Changes in bank governance have sought to temper the risk-taking behaviour of bank owners (Caprio et al., 2007; Laeven and Levine, 2009). Recent evidence suggests ownership structures help explain differences in the performance of Latin American financial institutions (Servin et al., 2012). In order to examine the evolution of bank cost efficiency in Latin America’s four largest economies, we construct an unbalanced panel data set of banks for the period 1985-2010. The sample comprises 409 commercial banks, and 4,572 bank-year observations. We estimate stochastic frontier cost functions using pooled data for the four countries.

A potential problem associated with the common frontier approach, in which the best practice frontier is made up of the best performing banks from the set of countries under review, is that differences in measured efficiency may reflect differences between countries in the economic environment (Dietsch and Lozano-Vivas, 2000; Berger, 2007). Our controls for the economic environment include weighted averages of several descriptors of banking sector characteristics, to avoid possible endogeneity problems (Berger and Mester, 1997), and other financial sector and macroeconomic indicators. We report average rank efficiencies on an annual basis, drawn from a common frontier (Berger et al., 2004), and disaggregated by ownership type (state-owned, privately-owned, and foreign-owned). Average rank cost efficiency declined between the late-1980s and the mid-1990s, and then improved during the 2000s prior to the onset of the subprime crisis in 2007. The impact of this crisis on bank efficiency has varied widely between countries, and by bank ownership type. The average rank cost efficiencies for 2009 and 2010, however, suggest that performance has recovered to some extent.

The remainder of the paper is organized as follows. Section 2 examines factors believed to affect bank efficiency in Latin America. Section 3 presents the stochastic cost frontier specification and estimation. Section 4 describes that data. Section 5 reports results from the Monte Carlo simulation exercise. Section 6 compares the cost function estimations obtained from a number of model specifications. Section 7 interprets the results for the evolution of bank efficiency in Latin America. Finally, Section 8 concludes.

2. Factors affecting bank efficiency in Latin America

Over the past thirty years the industrial structures of many Latin American banking sectors have been transformed by a fundamental shift towards liberal economic and financial policies. Institutional environments and regulatory structures have evolved, affecting the efficiency of banking operations in ways that impact on performance differentials between countries (Barth et al., 2013; Gaganis and Pasiouras, 2013). Policies intended to promote competition in banking are justified on the basis that competitive pressure provides incentives for improvements in efficiency, which in turn may enhance financial stability (Schaeck and Cihák, 2013). Thus, deregulation constitutes an exogenous shock which pressurizes banks to reduce costs. Better managed (more efficient) banks gain market share at the expense of inefficient rivals, increasing industry concentration as larger banks acquire smaller ones (Demsetz, 1973). It is important for policymakers to identify changes in market power, and monitor how these affect efficiency, because market power provides opportunities to raise prices. Competition could be reduced if bank executives opt for a quiet life, and forgo the rents that are potentially available through increased efficiency (Berger and Hannan, 1998). In emerging markets, a combination of market power and industry concentration could retard both financial deepening and efficiency gains (Rojas Suarez, 2007). On the contrary, competition may adversely affect efficiency through poor management, if banks are not adept at screening and monitoring customers, and non-performing loans are allowed to accumulate (Berger and DeYoung, 1997).

Competition in Latin American banking has been characterized previously as monopolistic competition (IMF, 2001; Gelos and Roldós, 2004). Across Latin America, consolidation significantly reduced the number of banks, following major restructuring in response to the mid-1990s banking crises (Domanski, 2005). Between 1994 and 2000, bank numbers fell by 45% in Argentina; 21% in Brazil; 22% in Chile; and 36% in Mexico. Between 1994 and 2000 the three-firm concentration ratio increased by around 5 and 8 percentage points in Brazil and Mexico, reaching 55% and 56%, respectively. In Argentina and Chile over the same period, the three-firm concentration ratio remained constant at around 40%.

Previous studies have failed to find evidence of collusion between banks (Yildirim and Philippatos, 2007, Yeyati and Micco, 2007). Nevertheless, there are cross-country differences in the intensity of competition (Gelos and Roldós, 2004; Yildirim and Philippatos, 2007). Some studies highlight difficulties in generalizing results both within and between countries; for example, national-level findings fail to generalize for banks in different size categories in the case of Brazil (Belaisch, 2003), and Argentina and Chile (Yildirim and Philippatos, 2007). Competition may vary according to bank ownership: in Brazil, the behaviour of small banks and public banks is characterized by the model of monopolistic competition; large banks and foreign banks by perfect competition; and privately-owned banks conform more closely to the model of perfect competition than state-owned banks (Coelho et al., 2007). Chortareas et al. (2011) suggest that abnormal profits in Argentinean, Brazilian and Chilean banking are driven by efficiency advantages, rather than anti-competitive or collusive behaviour. In a study of 17 Latin American banking markets, Tabak et al. (2013) show that the cost efficiency differential between large and small banks increases with an increase in industry concentration. This suggests that large banks do not present a too-big-to-fail problem for bank regulators.

Policy reforms have diminished the role of the state, through measures such as privatization and liberalization of foreign entry requirements. In the early 1990s, state-owned banks controlled between 45 and 50 per cent of bank assets in Argentina and Brazil, and 100 per cent in Mexico following nationalization of the banking industry in 1982 (Haber, 2005). State-owned banks were typically characterized by poor loan quality, under-performance, and weak cost control (Cornett et al., 2010). According to Ness (2000), divergence between the economic and political goals of government and the business goals of banks gave rise to moral hazard problems. The large size of public banks conferred too-big-to-fail status, requiring frequent use of public funds to support ailing institutions. Accordingly, agency problems may explain differences in performance between domestic state-owned and privately-owned banks, as well as cross-border performance differences (Megginson, 2005). Formerly, state ownership was extensive in Argentina and Brazil, but privatization transferred the majority of state-owned banks into a private sector that was expected to manage the assets more efficiently (Carvalho et al., 2009). Evidence on the impact of privatization is mixed, however. Performance improved post-privatization in Argentina (Berger et al., 2005) and Brazil (Nakane and Weintraub, 2005); but the estimated cost of a (failed) bank privatization programme in Mexico in 1991-92 was $65 billion (Haber, 2005).

The impact of liberalization on competition is influenced by the extent of foreign bank penetration, and restrictions on entry and permissible activities (Claessens and Levine, 2004). To facilitate competition and recapitalize distressed banks, many governments have lifted restrictions on foreign bank entry. In 1990, Chile had the highest level of foreign bank penetration among the four Latin American countries examined in this study, amounting to 19% of banking industry assets. This figure had increased to 42% by 2004. Foreign banks in Mexico held only 2% of assets in 1990, but 82% in 2004. The growth in Argentina over the same period was from 10% to 48%, and in Brazil from 6% to 27% (Domanski, 2005).

Foreign bank acquisition of domestic banks is often explained by the superior management skills and technological capabilities of the former, which permit the export of efficiency improvements to the host country (Berger et al., 2000). Foreign bank entry is expected to enhance performance throughout the host country banking sector, because domestic banks must achieve efficiency gains or face losing market share (Claessens et al., 2001). However, operational diseconomies associated with distance from the home headquarters, and cultural differences between home and host countries, can raise costs and reduce the efficiency of foreign banks (Berger et al., 2000; Mian, 2006).

There is evidence that the entry into Latin America of foreign banks that were more efficient and less risky than their domestic counterparts increased the intensity of competition, with positive spillover effects for local banks (Jeon et al., 2011; Olivero et al., 2011). Foreign acquirers focused on restructuring and integrating operations with the parent (foreign) bank (Clarke et al., 2005), leading to improvements in credit risk management and other resource allocation advantages (Crystal et al., 2002). Foreign bank penetration can, however, impact negatively on the performance of domestic banks, if foreign institutions cherry-pick the best customers, forcing local banks to service higher risk and more costly customers (Dages et al., 2002; Paula and Alves, 2007; Jeon et al., 2011). In Argentina and Mexico, foreign banks concentrated lending in the commercial loans market, and limited their exposure to the household and mortgage sectors (Dages et al., 2002; Paula and Alves, 2007).

Foreign bank acquisitions in Argentina used growth in lending to diversify away from manufacturing, and target consumers (Berger et al., 2005). In addition, foreign banks focused aggressively on regional markets, taking advantage of changes in local banks' lending (Clarke et al., 2005).

3. Stochastic cost function specification and estimation

In order to examine the influence of cross-firm heterogeneity on bank inefficiency estimates we start by estimating the traditional stochastic cost frontier, widely used in the literature, as a benchmark. The stochastic frontier production function (see Aigner et al, 1977; Meeusen and van den Broeck, 1977) specifies a two-component error term that separates inefficiency and random error. In the two-component error, a symmetric component captures random variation of the frontier across banks, statistical noise, measurement error, and exogenous shocks beyond managerial control. The other component is a one-sided term that measures inefficiency relative to the frontier. Let c_{it} denote the natural logarithm of total cost for bank i in year t (normalized as described below), let $\mathbf{x}_{it}$ denote a $(k_x \times 1)$ vector of output, input price, and time variables, and let $\varepsilon_{it} = v_{it} + u_{it}$ denote the two-component disturbance term. The baseline model is

$$c_{it} = \alpha + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} + u_{it} \qquad [1]$$

where the random component of ε_{it} is $v_{it} \sim N(0, \sigma_v^2)$; and the inefficiency component is $u_{it} = |U_{it}|$, where $U_{it} \sim N(0, \sigma_u^2)$.

The total variance of ε_{it} is $\sigma^2 = \sigma_v^2 + \sigma_u^2$. The contribution of the random component to the total variance is $\sigma_v^2 = \sigma^2/(1+\lambda^2)$; and the contribution of the inefficiency component is $\sigma_u^2 = \sigma^2\lambda^2/(1+\lambda^2)$, where $\lambda = \sigma_u/\sigma_v$ reflects the relative contributions of u and v to ε_{it}. The Jondrow et al. (1982) estimator of u_{it} is based on the conditional expectation of u_{it} given the realized value of ε_{it}:

$$\hat{u}_{it} = E(u_{it} \mid \varepsilon_{it}) = \frac{\sigma\lambda}{1+\lambda^2}\left(\frac{\phi(a_{it})}{1-\Phi(a_{it})} - a_{it}\right)$$

where $a_{it} = \varepsilon_{it}\lambda/\sigma$, and $\phi(\ )$ and $\Phi(\ )$ are the density and distribution functions, respectively, for the standard normal distribution.

The availability of panel data sets boosted developments in the frontier literature. Early approaches modelled inefficiency as time-invariant, a very restrictive assumption particularly in panels with a long time dimension. Kim and Schmidt (2000) and Schmidt and Sickles (1984) recast [1] as a fixed effects model, as follows:

$$c_{it} = \alpha_i + \boldsymbol{\beta}'\mathbf{x}_{it} + v_{it} \qquad [2]$$

where the inefficiency term for each bank is assumed to be constant over time, so $u_{it} = u_i$ for all i,t, and $\alpha_i = \alpha + u_i$. Fixed effects estimation requires no distributional assumptions concerning u_i. A simple inefficiency estimator is given by $\hat{\alpha}_i - \min_i(\hat{\alpha}_i)$. Greene (2008) reviews the early panel data methods. Later panel data methods remove the limitation of a time-invariant inefficiency term. Other challenges remained, including the key issue of how to treat observed and unobserved heterogeneity. Observed heterogeneity can be incorporated into the cost function by specifying variables such as a time trend and/or other control factors. Their inclusion affects 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.

Unobserved heterogeneity presents a greater challenge. Generally, it enters the stochastic frontier through either fixed or random effects. This approach can confound cross-firm heterogeneity with the inefficiency term, leading to biased estimates. Greene (2005a,b) solves this problem by extending both fixed and random effects models to account for unobserved heterogeneity. The literature refers to these random parameters models as "true" effects models.

In this study, our strategy is to estimate a number of alternative specifications of the stochastic frontier cost function. Equation (1) is the baseline specification, referenced Model 1 below, and estimated using OLS. Equation (2) is the fixed effects specification, referenced Model 2. Models 3 to 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 reported below, the parameters 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 parameters are linear in average asset size. The parameters 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 used to define the inefficiency term is assumed to be linear in asset size. The parameter on asset size is assumed to be random with a constant mean. The most general model specification is as follows:

$c_{it} = \alpha_{it} + \boldsymbol{\beta}_i'\mathbf{x}_{it} + \boldsymbol{\phi}'\mathbf{y}_{it} + v_{it}$, where $\alpha_{it} = \alpha_i + u_{it}$

$v_{it} \sim N(0, \sigma_v^2)$, where σ_v^2 is constant

$u_{it} = |U_{it}|$, where $U_{it} \sim N(0, \sigma_{ui}^2)$ and $\sigma_{ui} = \sigma_u \exp(\theta_i)$

$(\alpha_i\ \boldsymbol{\beta}_i')' = (\bar{\alpha}\ \ \bar{\boldsymbol{\beta}}')' + \boldsymbol{\Delta}_{\alpha,\beta}\, s_i + \boldsymbol{\Gamma}_{\alpha,\beta}\, (w_{\alpha i}\ \ \mathbf{w}_{\beta i}')'$

$$\theta_i = \bar{\theta} + \delta_\theta s_i + \gamma_\theta w_{\theta i} \qquad [3]$$

where $\mathbf{x}_{it}$ is defined as before; $\mathbf{y}_{it}$ is a ($k_y \times 1$) vector of other cost function covariates; and s_i is the average asset size of bank i. The parameter vectors are as follows: $(\alpha_i\ \boldsymbol{\beta}_i')'$ is a ($k_x+1 \times 1$) vector of random parameters; $(\bar{\alpha}\ \bar{\boldsymbol{\beta}}')'$ and $\boldsymbol{\Delta}_{\alpha,\beta}$ are ($k_x+1 \times 1$) vectors of (fixed) parameters; $\boldsymbol{\Gamma}_{\alpha,\beta}$ is a free ($k_x+1 \times k_x+1$) lower-triangular matrix of (fixed) parameters; $\boldsymbol{\phi}$ is a ($k_y \times 1$) vector of (fixed) parameters; θ_i is a random parameter; $\overline{\theta}$ and γ_θ are (fixed) parameters. ($w_{\alpha i}$ $\mathbf{w}_{\beta i}'$)' is a ($k_x+1\times 1$) vector of NIID random disturbances, where $\mathbf{w}_{\beta i}' = \{w_{\beta ji}\}$ for j=1,..., k_x; and $w_{\theta i}$ is a NIID random disturbance. The individual elements of the parameter vectors are denoted as follows: $\boldsymbol{\beta}_i' = \{\beta_{ji}\}$, $\overline{\boldsymbol{\beta}}' = \{\overline{\beta}_j\}$ for j=1,..., k_x; $\boldsymbol{\Delta}_{\alpha,\beta}' = \{\delta_j\}$ for j=0,..., k_x; $\boldsymbol{\phi}' = \{\phi_j\}$ for j=1,..., k_y; and $\boldsymbol{\Gamma}_{\alpha,\beta} = \{\gamma_{jh}\}$ for j=0,..., k_x and h=0,...,j. The specification of $\boldsymbol{\Gamma}_{\alpha,\beta}$ implies the variances of the random parameters, either unconditional or conditional on s_i, are $\text{var}(\alpha_i) = \gamma_{00}^2$, $\text{var}(\beta_{ji}) = \sum_{h=0}^{j}\gamma_{jh}^2$, $\text{var}(\theta_i) = \gamma_\theta^2$ (with equivalent definitions for the conditional variances $\text{var}(\alpha_i|s_i)$, $\text{var}(\beta_{ji}|s_i)$ and $\text{var}(\theta_i|s_i)$). The corresponding standard deviations are denoted $\sigma(\alpha_i)$ or $\sigma(\alpha_i|s_i)$, and so on. The specification of $\boldsymbol{\Gamma}_{\alpha,\beta}$ allows for non-zero conditional covariances between the elements of (α_i $\boldsymbol{\beta}_i'$)'. We report estimations of several restricted versions of [3]:

Model 3: Random (individual) effects with homogeneous means. The restrictions on [3] are: $\{\delta_j\} = 0$ for j=0,..., k_x; $\{\gamma_{jk}\} = 0$ for j=1,..., k_x, k=0,...,j; and $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$.

Model 4: Random effects and random parameters on the output, input, and time variables. The restrictions on [3] are: $\{\delta_j\} = 0$ for j=0,..., k_x; and $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$.

Model 5: Random effects and random parameters on the output, input, and time variables with heterogeneous means linear in average asset size. The restrictions on [3] are: $\overline{\theta} = \delta_\theta = \gamma_\theta = 0$.

Model 6: Random effects and random parameters on the output, input, and time variables with homogeneous means, and a random parameter with a heterogeneous mean linear in average asset size for the log standard deviation of the half-normal distribution used to define the inefficiency term. The restrictions on [3] are: $\{\delta_j\} = 0$ for j=0,...,k_x.

The stochastic frontier cost functions are estimated using 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_i 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 characterized by arbitrary assumptions, and it is not always possible to carry out formal statistical tests between alternatives; for instance, the random parameters models we estimate are not nested.

4. 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 industry is represented by the translog functional form. A unique feature of this study is the construction of a panel data set covering over a quarter of a century from 1985 to 2010 for banks from Argentina, Brazil, Chile and Mexico. Financial statements data are sourced from the IBCA and BankScope databases. Data are deflated by national GDP deflators and converted in US$ millions at 2000 prices. The dimension of the data set is 419 banks and 4,571 bank-year observations over 26 years. Bank ownership is identified using BankScope, central bank reports, academic papers, newswire services, and bank web sites. The macroeconomic data are from the World Bank Financial Indicators and World Economic Outlook databases. Table 1 reports descriptive statistics for the sample banks.

Table 1 here

The cost function includes three outputs defined in value terms (loans, deposits, and other earning assets), and three input prices (for 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 specification rests on an assumption of a common production technology for all banks, which 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 the model specification 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 including linear and quadratic time trends, denoted T and T^2 below, and interactions between time and the outputs, and between time and the input prices. The sum of the estimated parameters on the time variables measures the effect of technical change in production on bank cost.[1] We control for the impact of cross-country differences on bank cost by specifying a vector of banking sector and economic control variables at country level (see Appendix).

The dependent variable of the cost function is defined as the natural logarithm of variable cost (the sum of interest paid, personnel expense and non-interest expense). The outputs and input prices, with all terms in logarithmic form, are defined as follows: q_{1it}=loans; q_{2it}=deposits; q_{3it}=other earning assets; $\tilde{p}_{1it}$ =interest paid/purchased funds; $\tilde{p}_{2it}$ =non-interest expenses/fixed assets; $\tilde{p}_{3it}$ =personnel expense/total assets. Cost and two of the input prices are normalized by dividing by the third input price, as follows: $c_{it} = \tilde{c}_{it} - \tilde{p}_{3it}$; and $p_{lit} = \tilde{p}_{lit} - \tilde{p}_{3it}$ for l=1,2. With reference to [1], [2] and [3], the k_x=27 elements of $\mathbf{x_{it}}$ are: q_{hit} for h=1,2,3; p_{lit}

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

for l=1,2; $q_{hit}q_{lit}$ for h=1,2,3, l=1,…,h; $p_{hit}p_{lit}$ for h=1,2, l=1,…,h; $q_{hit}p_{lit}$ for h=1,2,3, l=1,2; T, T^2; $q_{hit}T$ for h=1,2,3; and $p_{lit}T$ for l=1,2.

The country- and industry-level controls, which comprise the k_y=9 elements of $\mathbf{y_{it}}$, are defined as follows:

ETA = weighted annual average of the ratio of equity-to-assets to proxy capitalization;
Z = weighted annual average of the Z score expressed as ln(Z+100), Z calculated using a 4-year rolling window;
HHI = natural logarithm of the Herfindahl-Hirschman index of total assets;
LLR = weighted annual average of the ratio of loan loss reserves-to-gross loans;
DIV = weighted annual average of the diversification index;
GDP = log real gross domestic product per capita;
ΔGDP = annual rate of GDP growth;
CR = ratio of bank credit to the private sector-to-GDP;
SO = ratio of state-owned bank assets-to-total banking industry assets.

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 data set.

5. Choice between random effects and random parameters cost frontier specifications

The availability of several model specifications derived from [3] naturally raises questions concerning the accuracy of the estimated inefficiency scores under the alternative specifications that might be selected for the estimation. In particular, we may wish to compare the accuracy of the estimation procedure in identifying the true inefficiency scores when the estimated model specification corresponds to the true data generating process for the cost function, and when the estimated model differs from the true data generating process. In this subsection we report the results of an investigation, based on a small Monte Carlo simulation exercise, which provides comparisons of this kind that are indicative rather than comprehensive.

Our investigation focuses on the comparison between Models 3 and 4, with the additional parameter restrictions $\boldsymbol{\phi}=\mathbf{0}$ imposed. For convenience, the concise model specification (as in [3] but with the relevant parameter restrictions imposed), is as follows:

$c_{it} = \alpha_{it} + \boldsymbol{\beta}_i'\mathbf{x}_{it} + v_{it}$, where $\alpha_{it} = \alpha_i + u_{it}$

$v_{it} \sim N(0, \sigma_v^2)$, where σ_v^2 is constant

$u_{it} = |U_{it}|$, where $U_{it} \sim N(0, \sigma_u^2)$, where σ_u^2 is constant

$$(\alpha_i \ \boldsymbol{\beta}_i')' = (\bar{\alpha} \ \ \bar{\boldsymbol{\beta}}')' + \boldsymbol{\Gamma}_{\alpha,\beta}(w_{\alpha i} \ \ \mathbf{w}_{\beta i}')' \quad [4]$$

For both Models 3 and 4, $\gamma_{00} \neq 0$. For Model 3 $\{\gamma_{jh}\} = 0$ and for Model 4 $\{\gamma_{jh}\} \neq 0$, for j=1,...,k_x, h=0,...,j. For the case where the true data generating process corresponds to Model 3, we examine the performance of the estimation procedure in identifying the true inefficiency scores: (i) when the specification of the estimated model corresponds to Model 3 so that the estimated model is correctly specified; and (ii) when the specification of the estimated model corresponds to Model 4 so that the estimated model is over-parameterized. Similarly, for the case where the true data generating process corresponds to Model 4, we examine the performance of the estimation procedure in identifying the true inefficiency scores: (iii) when the specification of the estimated model corresponds to Model 3 so that the estimated model is mis-specified and under-parameterized; and (iv) when the specification of the estimated model corresponds to Model 4 so that the estimated model is correctly specified.

The Monte Carlo simulations are structured as follows. For each repetition, in the simulated data set the numbers of bank (cross-sectional) observations, and time series observations on each bank, correspond exactly to the sample values. We construct two sets of simulated values of c_{it}, generated in accordance with data generating processes corresponding to Models 3 and 4 respectively, using the sample values of $\mathbf{x_{it}}$, the estimated values of ($\overline{\alpha}$ $\overline{\beta}$), γ_{00} and $\{\gamma_{jh}\}$ (for Model 4 only), and randomly generated values for v_{it} and u_i drawn from normal distributions with zero mean and variances equivalent to the estimated σ_v^2 and σ_u^2. We then estimate the cost function and inefficiency scores for c_{it} generated in accordance with Model 3, (i) using Model 3 as the estimated model, and (ii) using Model 4; and for c_{it} generated in accordance with Model 4, (iii) using Model 3 as the estimated model, and (iv) using Model 4. For each of (i) to (iv) we assess the performance of the estimated model in replicating the true inefficiency scores by examining the Pearson correlation between the true u_{it} and the estimated $\hat{u}_{it}$.

Table 2 reports summary statistics for the Pearson correlations between u_{it} and $\hat{u}_{it}$ obtained from 50 replications of the procedure described above. For the case where the data generating process for c_{it} corresponds to Model 3, the average correlation is 0.33 in both cases. The choice of specification for the estimated model makes little or no difference to the capability of the estimation procedure to identify the true inefficiency scores. Applying random parameters estimation (Model 4) to data generated in accordance with the random effects model (Model 3) generally produces very small estimated standard deviations for the random parameters. The estimated random parameters model is therefore very similar to a random effects model, and the estimated inefficiency scores are similar as well.

Table 2 here

By contrast, for the case where the data generating process for c_{it} corresponds to Model 4, the average correlation is substantially lower, around 0.14 for estimation using Model 3, and 0.18 for estimation using Model 4. If the data generating process is random parameters, rather than random effects, the relationship between $\mathbf{x_{it}}$, $\mathbf{y_{it}}$ and c_{it} is noisier and more difficult to disentangle, making it harder for the estimation procedure to identify efficiency. Furthermore, by applying random effects estimation (Model 3) to data generated in accordance with the random parameters model (Model 4), the cost function used in the estimation is mis-specified, with a deleterious effect on the capability of the estimation procedure to identify the true inefficiency scores.

The main implication of this investigation is that cost function estimation using a specification that is over-parameterized results in little or no loss of performance in estimating inefficiency, while estimation using a specification that is under-parameterized and therefore misspecified results in a substantial loss of performance. Accordingly in the estimations reported in the following sections, we place greater emphasis on the more richly parameterized specifications.

6. Estimated parameters of stochastic frontier cost functions

This section reports and interprets the parameter estimates, variances, and estimated inefficiency scores from the stochastic frontier cost function models. Table 3 reports the estimated parameters for Models 1 to 3, and Table 4 for Models 4 to 6.

Tables 3 and 4 here

We begin by reviewing the estimated parameters of the stochastic frontier cost functions. In line with expectations, the parameters on the output and input terms are positive and significant in all of the specifications. The estimated σ_u is substantially larger for the standard Model 1 than the estimated σ_u for the random effects and random parameters Models 3 to 6, suggesting that heterogeneity and inefficiency are confounded in the standard model. The estimated σ_u are similar in magnitude across Models 4 to 6, and the same applies to the estimated σ_v. The dispersion in mean cost inefficiency estimates reported in the literature suggests that choices concerning estimation technique, sample selection and observation period bear importantly on measured inefficiency (Berger and Humphrey, 1997; Bauer et al., 1998). Table 5 reports the distributional properties of the estimated cost efficiencies from each model. Defining efficiency by subtracting the cost inefficiency score from one, the mean estimated cost efficiency obtained from Models 3 to 6 varies from 83% to 87%. In contrast, the mean estimated cost efficiency obtained from Model 1 is around 74%. The standard deviation of the estimated cost efficiencies obtained from Model 1 is almost twice the magnitude of the corresponding standard deviations for Models 3 to 6. Model 2 (fixed effects) yields the lowest mean estimated cost efficiency of around 56%. The standard deviation for Model 2 is below the standard deviation for Model 1, but exceeds the standard deviations for Models 3 to 6.

Table 5 here

Bauer et al. (1998) suggest that measured efficiencies derived from alternative approaches should comply with a set of consistency conditions. For example, estimated efficiencies obtained from alternative model specifications or estimation methods should have similar means, standard deviations, and other distributional properties; and the efficiency rankings of the subjects should be approximately the same. Table 6 reports the Spearman rank order correlation parameters for each available pairing of ranked estimated inefficiency scores, obtained from Models 1 to 6. The most closely matched pairing is for Models 4 and 5, but all of the reported rank order correlations are significant at the 0.01 level.

Table 6 here

7. Evolution of cost efficiency

Thus far we demonstrate that random parameters models better accommodate heterogeneity. This section presents an analysis of cost efficiency using the estimated inefficiency scores obtained from Model 5 that are highly correlated with the scores from Model 4 (0.8299). (Using efficiencies from Models 4 and 6 does not affect the findings that we report here.) To compare inter-country efficiencies over time, we convert the estimated efficiencies into rank order from zero to 100 (Berger et al., 2004). For example, the average rank cost efficiency of Argentinean banks is 26.45 in 1985, implying that the average Argentine bank is more cost efficient than 26% of all sample banks between 1985 and 2010.

Figure 1 shows the evolution of average rank cost efficiency by country and year. Across the four countries, cost efficiency was volatile between the mid-1980s and early 1990s, a period of macroeconomic uncertainty and weak institutional environments. Barth et al. (2013), Gaganis and Pasiouras (2013) and Tabak et al. (2013) suggest public policy should be directed towards strengthening institutions and regulation in order to enhance efficiency and financial stability. However, the average rank cost efficiency for each country for the period 1985 to 1993 exceeds the corresponding average (for the same country) for 1994 to 2000. The mid-1990s banking crises appear to have had a damaging effect on bank efficiency: for example, the average rank cost efficiency of Mexican banks fell from 58.14 (1985-93) to 45.73 (1994-2000).

Average rank cost efficiency for each country improved between 1994-2000 and 2001-2006. This finding supports claims that reforms to promote competition are capable of inducing efficiency gains (Schaeck and Cihák, 2013), and is consistent with the efficient structure hypothesis but inconsistent with the quiet life hypothesis (see Koetter et al., 2012 for the US; and Williams, 2012 for Latin America). Argentina records the largest improvement in mean rank cost efficiency, from 50.42 (1994-2000) to 59.00 (2000-2006).

The mean rank cost efficiencies for 2007 to 2010 suggest the impact of the global banking crisis on average cost efficiency differed widely between Latin American countries. For example, the mean rank cost efficiency was reduced from 59.00 (2000-2006) to 40.65 (2007-2010) for Argentina and from 51.77 (2000-2006) to 41.30 (2007-2010) for Mexico. By contrast, the mean rank cost efficiencies for Brazil and Chile were only marginally smaller for 2007-2010 than for 2001-2006. In explanation, we refer to studies that report large reductions in bank lending, and attribute cross-country variations in bank performance to the contrasting policies of private, foreign and state-owned banks, and to inter-country differences in the extent to which state-owned banks were required to support bank lending (Cull and Pería, 2013; Carvalho, 2013).

Figure 1 here

Figures 2 and 3 trace the mean rank cost efficiencies of state-owned and privately-owned banks by country and year. For foreign-owned banks, Figures 4 and 5 trace the mean rank cost efficiencies of *de novo* entrants and entrants through merger and acquisition. State ownership is widely characterized by lower efficiency, attributed to moral hazard and other agency problems associated with public ownership (Ness, 2000; Megginson, 2005; Cornett et al., 2010). The decline in mean rank cost efficiency between 1985-1993 and 1994-2000 is unsurprising, in view of the formerly high levels of state ownership, and the impact of the mid-1990s banking crises that required extensive government intervention. Berger et al. (2005) attribute the under-performance of state-owned banks in Argentina to poor loan quality associated with direct lending and subsidised credit. The mean rank cost efficiencies of state-owned banks for 1985-93 were 53.32 (Argentina), 52.45 (Brazil), and 60.68 (Mexico). The corresponding 1994-2000 averages were 47.88 (Argentina), 45.97 (Brazil), and 52.24 (Mexico).

For Brazil, our results indicate an improvement in the mean rank cost efficiency of state-owned banks during the period 2001-2006, in comparison with 1994-2000. This improvement was sustained in 2007-2010. Similar evidence is reported by Nakane and Weintraub (2005) and Tecles and Tabak (2010). That Brazilian public banks remained relatively cost efficient demonstrates the strategic role these banks played during the sub-prime crisis (Carvalho, 2013). By contrast, the mean rank cost efficiency of state-owned banks in Argentina deteriorated sharply between 2001-2006 and 2007-2010.

Figure 2 here

Our results shed some light on bank privatization outcomes. In both Argentina and Brazil, the high fiscal costs associated with poorly performing state-owned banks prompted the decision to privatize (Clarke et al., 2005; Nakane and Weintraub, 2005). Although the state-owned banks were substantially restructured prior to privatization, there remains the assumption that private ownership will deliver a more efficient outcome. The mean rank cost efficiency of privately-owned banks in both Argentina and Brazil was stable between 1985-1993 and 1994-2000. By contrast, the mean rank cost efficiency of privately-owned banks in Mexico declined faster than that of state-owned banks. Berger et al. (2005) acknowledge the positive contribution of privatization in Argentina, but note also that merger and acquisition failed to produce a similar effect, consistent with our findings.

Figure 3 here

Generally, the mean rank cost efficiency of privately-owned banks improved between 1994-2000 and 2001-2006: in ascending order, by 16.4 percentage points (p.p.) in Mexico, 9.2 p.p. in Argentina, 6.8 p.p. in Chile, and less than 1 p.p. in Brazil. Only in Chile did privately-owned banks improve in terms of mean rank cost efficiency between 2001-2006 and 2007-2010, by 4.4 p.p. The mean rank cost efficiency fell in Brazil by 2.7 p.p. and more substantially in Argentina and Mexico (by 24.4 and 18.3 p.p., respectively). As noted above, many privately-owned banks reduced lending, with harmful effects for measured efficiency (Cull and Pería, 2013).

Although there is evidence that foreign bank entry leads to enhanced banking industry performance (Claessens et al., 2001) there are some caveats: for example, one needs to distinguish between the performance of existing foreign banks and local banks acquired by foreign banks. Differences in the level of foreign bank penetration can produce varying outcomes for competition, which subsequently influence efficiency. Figure 4 shows that the mean rank cost efficiency of *de novo* foreign entrants follows a similar pattern to state-owned and privately-owned banks; average performance declines between 1985-1993 and 1994-2000. The efficiency of *de novo* entrants improved by 9.6 and 8.3 p.p. in Argentina and Brazil between 1994-2000 and 2001-2006, increased by 1.6 p.p. in Chile, and decreased by 18.4 p.p. in Mexico. Between 2001-2006 and 2007-2010, the efficiency of *de novo* entrants fell in all countries except Chile. The largest reduction was in Argentina (by 13.2 p.p.), with more modest reductions in Brazil (less than 1 p.p.) and Mexico (3.2 p.p.). Although *de novo* entrants were marginally more cost efficient than foreign bank acquisitions during 2007-2010 (with the exception of Mexico), this pattern does not generalize to other periods. The results for Brazil are consistent with the hypothesis that foreign bank entry through merger and acquisition typically fails to realize efficiency gains, because foreigners often acquire formerly distressed banks (Fachada, 2008).

Figure 4 here

Foreign acquisition of Latin American banks accelerated during 1994-2000. The mean rank cost efficiencies for this cohort suggest efficiency gains between 1994-2000 and 2001-2006 in Argentina (5.7 p.p.), Chile (15.8 p.p.) and Mexico (37.4 p.p.), but not Brazil (decrease of 5.7 p.p.). Our findings support the claim that foreign bank penetration following restructuring increased the intensity of competition, particularly when more efficient and less risky foreign banks entered the market (Jeon et al., 2011). In general, the empirical evidence on foreign bank efficiency is varied. Although foreign banks are reported to be more efficient than state-owned banks (Crystal et al., 2002), several studies report little difference between the efficiencies of privately-owned banks and foreign banks (see Berger et al., 2005 for Argentina; Guimarães, 2002; Paula, 2002; and Vasconcelos and Fucidji, 2002 for Brazil). In Brazil foreign banks faced difficulties in adapting to the peculiarities of the Brazilian banking market, which is dominated by local, private-owned banks (Paula, 2002). This is unsurprising, since the operational characteristics and balance sheets of domestic and foreign banks are similar, suggesting that the benefits of foreign penetration materialise slowly (Carvalho, 2002; Paula and Alves, 2007). Elsewhere, Tecles and Tabak (2010) finds foreign banks in Brazil less cost efficient than privately-owned and state-owned banks.

Figure 5 here

Finally, we examine the cost efficiency of foreign acquired banks during 2007-2010. Historically, foreign banks in Latin America have been able to withstand banking crises, helping to maintain market liquidity and stabilise lending (Dages et al., 2002; Crystal et al., 2002). In some countries, however, foreign banks (and privately-owned banks) reduced lending significantly during the sub-prime crisis (Cull and Pería, 2013). This could explain the deterioration in the mean rank cost efficiency of foreign-acquired banks between 2001-2006 and 2007-2010 of 21.3, 9.8 and 5 p.p. in Argentina, Chile and Mexico, respectively. Only in Brazil did foreign-acquired banks improve mean rank cost efficiency (4.2 p.p.).

8. Conclusion

This paper contributes to the bank efficiency literature, through its application of recently developed random parameters models for stochastic frontier analysis. We estimate fixed and random effects models, and several alternative specifications of a random parameters model that accommodate various forms of heterogeneity. Using Monte Carlo simulations, we demonstrate that cost function estimation using an over-parameterized specification results in little or no loss of performance in estimating inefficiency, whereas estimation using a specification that is under-parameterized results in a substantial loss of performance. Estimated inefficiency scores obtained from random parameters models are higher, and arguably more precise, because heterogeneity is not confounded with inefficiency. Previous studies of bank cost efficiency based on panel data, which fail to control for heterogeneous cost function parameters, may have tended to underestimate efficiency.

The evolution of mean rank cost efficiency for banks from four Latin American countries between 1985 and 2010 is examined, using results obtained from a random parameters cost function specification. Average cost efficiency is found to have deteriorated between 1985-1993 and 1994-2000, and this pattern was especially pronounced for state-owned banks. Prior to 2006, Latin America witnessed widespread foreign bank expansion, reflecting an improved operating environment. In general cost efficiency improved throughout this period, even for state-owned Brazilian and Argentinian banks. The impact of the sub-prime crisis on bank efficiency varied between countries, and by bank ownership type. Our results suggest, however, that Latin American banking has recovered from the worst effects of the sub-prime crisis.

References

Acharya, V., Hasan, I., Saunders, A., 2006. Should banks be diversified? Evidence from individual bank loan portfolios. Journal of Business 79, 3, 1355- 1412.

Aigner, D.J., Lovell, C.A.K., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. Journal of Econometrics 6, 21-37.

Altunbas, Y., Evans, L., Molyneux, P., 2001. Bank ownership and efficiency. Journal of Money, Credit and Banking 33, 4, 926-954.

Banker, R. D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30, 1078-1092.

Barros. C.P., Ferreira, C., Williams, J., 2007. Analyzing the determinants of performance of best and worst European banks: A mixed logit approach. Journal of Banking and Finance 31, 2189-2203.

Barros. C.P., Williams, J., 2013. The random parameters stochastic frontier cost function and the effectiveness of public policy: Evidence from bank restructuring in Mexico. International Review of Financial Analysis 30, 98-108.

Barth, J.R., Caprio Jr, G., Levine, R., 2001. Banking systems around the globe: do deregulation and ownership affect performance and stability? In: Mishkin, F.S. (Ed.), Prudential Supervision: What Works and What Doesn't, NBER Conference Report Series, University of Chicago Press, 31-88.

Barth, J.R., Lin, C., Ma, Y., Seade, J., Song, F.M., 2013. Do bank regulation, supervision and monitoring enhance or impede bank efficiency? Journal of Banking and Finance 37, 2879-2892.

Bauer, P.W., Berger, A.N., Ferrier, G.D., Humphrey, D.B., 1998. Consistency conditions for regulatory analysis of financial institutions: a comparison of frontier efficiency methods. Journal of Economics and Business 50, 85-114.

Belaisch, A., 2003. Do Brazilian banks compete? IMF Working Paper, WP/03/113.

Berger, A.N., Humphrey, D.B., 1992. Measurement and efficiency issues in commercial banking. In: Griliches, Z. (Ed.), Output Measurement in the Service Sectors. National Bureau of Economic Research, University of Chicago Press, 245-279.

Berger, A.N., DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. Journal of Banking and Finance 21, 849-870.

Berger, A.N., Humphrey, D.B., 1997. Efficiency of financial institutions: International survey and directions for future research, European Journal of Operational Research, 98,175-212.

Berger, A.N., Mester, L.J., 1997. Inside the black box: What explains differences in the efficiencies of financial institutions? Journal of Banking and Finance 21, 895-947.

Berger, A.N., Hannan, T.H., 1998. The efficiency cost of market power in the banking industry: A test of the "quiet life" and related hypotheses. The Review of Economics and Statistics LXXX, 3, 454-465.

Berger, A.N., DeYoung, R., Genay, H., Udell, G.F., 2000. Globalisation of Financial Institutions: Evidence from Cross-Border Banking Performance, Brookings-Wharton Papers on Financial Services 3, 23-158.

Berger, A.N., Hasan, I., Klapper, L., 2004. Further evidence on the link between finance and growth: An international analysis of community banking and economic performance. Journal of Financial Services Research 25, 2-3, 169-202.

Berger, A.N., Clarke, G.R.G., Cull, R., Klapper, L., Udell, G.F., 2005. Corporate governance and bank performance: A joint analysis of the static, selection, and dynamic effects of domestic, foreign, and state ownership. Journal of Banking and Finance 29, 2179-2221.

Berger, A.N., 2007. International comparisons of banking efficiency. Financial Markets, Institutions and Instruments 16, 3, 119-144.

Bos, J.W.B., Koetter, M., Kolari, J.W., Kool, C.J.M., 2009. Effects of heterogeneity on bank efficiency scores. European Journal of Operational Research 195, 251-261.

Caprio, G., Laeven, L., Levine, R., 2007. Governance and bank valuation. Journal of Financial Intermediation 16, 584-617.

Carvalho, D.R., 2013. The real effects of government-owned banks: Evidence from an emerging market. Journal of Finance, DOI: 10.1111/jofi.12130.

Carvalho, F.J.C., 2002. The recent expansion of foreign banks in Brazil: first results. Latin American Business Review 3, 4, 93-119.

Carvalho, F.J.C., Paula, L.F., Williams, J., 2009. Banking in Latin America. In Berger, A., Molyneux, P., Wilson, J. (Eds.), The Oxford Handbook of Banking, Oxford University Press, 868-902.

Chortareas, G.E, Garza-Garcia, J.G, Girardone C., 2011 Banking sector performance in Latin America: Market power versus efficiency. Review of Development Economics, 15, 307–325.

Clarke, G.R.G., Crivelli, J.M., Cull, R., 2005. The direct and indirect impact of bank privatization and foreign entry on access to credit in Argentina's provinces. Journal of Banking and Finance 29, 5-29.

Claessens, S., Demirgüç-Kunt, A., Huizinger, H., 2001. How does foreign bank entry affect domestic banking markets? Journal of Banking and Finance 25, 891-911.

Claessens, S., Laeven, L., 2004. What drives bank competition? Some international evidence. Journal of Money, Credit and Banking 36, 3, 563-583.

Coelho, C.A., de Mello, J.M.P., Rezende, L., 2007. Are public banks pro-competitive? Evidence from concentrated local markets in Brazil. Texto para Discssão. No. 551, Pontifícia Universidade Católica do Rio de Janeiro.

Cornett, M.M., Guo, L., Khaksari, S., Tehranian, H., 2010. Performance differences in privately-owned versus state-owned banks: An international comparison. Journal of Financial Intermediation 19, 74-94.

Crystal, J.S., Dages, B.G., Goldberg, L., 2002. Has foreign bank entry led to sounder banks in Latin America? Current Issues in Economics and Finance 8, 1, 1-6.

Cull, R., Pería, M.S.M., 2013. Bank ownership and lending patterns during the 2008-2009 financial crisis: Evidence from Latin America and Eastern Europe. Journal of Banking and Finance, DOI: http://dx.doi.org/10.1016/j.jbankfin.2013.08.017

Dages, B.G., Goldberg, L., Kinney, D., 2000. Foreign and domestic bank participation in emerging markets: Lessons from Mexico and Argentina. FRBNY Economic Policy Review 17-36.

Demsetz, H., 1973. Industry structure, market rivalry, and public policy. Journal of Law and Economics 16, 1-9.

Demsetz, R., Strahan, E. 1997. Diversification, Size, and Risk at Bank Holding Companies. Journal of Money, Credit and Banking 29, 3, 300 – 313.

Detragiache, E., Tressel, T., Gupta, P., 2008. Foreign banks in poor countries: Theory and evidence. Journal of Finance LXII, 5, 2123-2160.

Dietsch, M., Lozano-Vivas, A., 2000. How the environment determines banking efficiency: A comparison between French and Spanish industries. Journal of Banking and Finance 24, 85-1004.

Domanski, D., 2005. Foreign banks in emerging market economies: changing players, changing issues. BIS Quarterly Review, 69-81.

Fachada, P., 2008. Foreign banks' entry and departure: the recent Brazilian experience (1996-2006). Banco Central do Brasil Working Paper Series, 164, June.

Gelos, R.G., Roldós, J., 2004. Consolidation and market structure in emerging market banking systems. Emerging Markets Review 5, 39-59.

Farrell, M.J., 1957. The Measurement of Productive Efficiency. Journal of the Royal Statistical Society, Series A, 120, 3, 253-290.

Fiordelisi, F., Marques-Ibanez, D., Molyneux, P., 2011. Efficiency and risk in European banking. Journal of Banking and Finance 35, 1315-1326.

Fixler, D.J., Zieschang, K.D., 1992. User costs, shadow prices and the real output of banks. In: Griliches, Z. (Ed.), Output Measurement in the Service Sectors, National Bureau of Economic Research, University of Chicago Press, 218-243.

Gaganis, C., Pasiouras, F., 2013. Financial supervision regimes and bank efficiency: International evidence. Journal of Banking and Finance. DOI: http://dx.doi.org/10.1016/j.jbankfin.2013.04.026

Greene, W., 2005a. Fixed and random effects in stochastic frontier models. Journal of Productivity Analysis 23, 7-32.

Greene, W., 2005b. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. Journal of Econometrics 126, 269-303.

Greene, W.H., 2008. The econometric approach to efficiency analysis. In: Fried, H.O., Lovell, C.A.K., Schmidt, S.S. (Eds.), The Measurement of Productive Efficiency and Productivity Growth, Oxford University Press, 92-251.

Guimarães, P., 2002. How does foreign entry affect domestic banking market? The Brazilian case. Latin American Business Review 3, 4, 121-140.

Haber, S., 2005. Mexico's experiments with bank privatization and liberalization, 1991-2003. Journal of Banking and Finance 29, 2325-2353.

Hannan, T., Hanweck, G., 1988. Bank insolvency risk and the market for large certificates of deposit. Journal of Money, Credit and Banking, 20, 2, 203-211.

Jeon, B.N., Olivero, M.P., Wu, J., 2011. Do foreign banks increase competition? Evidence from emerging Asian and Latin American banking markets. Journal of Banking and Finance 35, 856-875.

Jondrow, J., Lovell, C.A.K., Materov, I.S., Schmidt, P., 1982. On estimation of technical inefficiency in the stochastic frontier production function model. Journal of Econometrics 19, 233-238.

Keeley, M., 1990. Deposit Insurance, Risk, and Market Power in Banking. American Economic Review 80, 5, 1183-1200.

Kim, Y., Schmidt, P., 2000. A review and empirical comparison of Bayesian and classical approaches to inference on efficiency levels in stochastic frontier models with panel data. Journal of Productivity Analysis 14, 2, 91–118.

Koetter, M., Kolari, J., Spierdijk, L., 2012. Enjoying the quiet life under deregulation? Evidence from adjusted Lerner indices for U.S. banks. Review of Economics and Statistics 94, 2, 462-480.

Laeven, L., Levine, R., 2009. Bank governance, regulation and risk taking. Journal of Financial Economics 93, 259-275.

Levine, R., 2005. Finance and Growth: Theory and Evidence. In Aghion, P., Durlauf, S. (eds) Handbook of Economic Growth edition 1, volume 1, chapter 12, pages 865-934 Elsevier.

Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from a Cobb-Douglas production function with composed error. International Economic Review 18, 435-444.

Megginson, W., 2005. The economics of bank privatisation. Journal of Banking and Finance 29, 8-9, 1931-1980.

Mester, L.J., 1996. A study of bank efficiency taking into account risk-preferences. Journal of Banking and Finance 20, 1025-1045.

Mester, L.J., 1997. Measuring Efficiency at US banks: Accounting for heterogeneity is important. European Journal of Operational Research 98, 230-424.

Mian, A., 2006. Distance constraints: The limits of foreign lending in poor economies. Journal of Finance LXI, 3, 1465-1505.

Nakane, M.I., Weintraub, D.B., 2005. Bank privatization and productivity: Evidence for Brazil. Journal of Banking and Finance 29, 2259-2289.

Nakane, M.I., Alencar, L.S., Kanczuk, F., 2006. Demand for bank services and market power in Brazilian banking. Working Paper No. 107, Banco Central do Brasil.

Nash, R., Sinkey, J., 1997. On competition, risk, and hidden assets in the market for bank credit cards. Journal of Banking and Finance, 21, 89-112.

Ness, W.L., 2000. Reducing government bank presence in the Brazilian financial system: Why and how. The Quarterly Review of Economics and Finance 40, 71-84.

Olivero, M.P., Li, Y., Jeon, B.N., 2011. Competition in banking and the lending channel: Evidence from bank-level data in Asia and Latin America. Journal of Banking and Finance, 35, 560-571.

Orea, L., Kumbhakar, S., 2004. Efficiency measurement using a latent class stochastic frontier model. Empirical Economics 29, 169-183.

Paula, L.F., 2002. Expansion strategies of European banks to Brazil and their impacts on the Brazilian banking sector. Latin American Business Review 3, 4, 59-91.

Paula, L.F., Alves Jr, A.J., 2007. The determinants and effects of foreign bank entry in Argentina and Brazil: a comparative analysis. Investigación Económica LXVI, 259, 63-102.

Rojas-Suarez, L., 2007. The provision of banking services in Latin America: Obstacles and recommendations. Working Paper No. 124, Center for Global Development.

Rossi, S.P.S., Schwaiger M.S., Winkler, G., 2009. How loan portfolio diversification affects risk, efficiency and capitalization: A managerial behavior model for Austrian banks, Journal of Banking and Finance, 33, 2218-2226.

Sanya, S., Wolfe, S., 2011. Can banks in emerging economies benefit from revenue diversification? Journal of Financial Services Research 40, 1-2, 79-101.

Schaeck, K., Cihák, M., 2013. Competition, efficiency and stability in banking. Financial Management. DOI: 10.1111/fima.12010.

Schmidt, P., Sickles, 1984. Production Frontiers with Panel Data. Journal of Business and Economic Statistics 2, 4, 367–374.

Sealey, C., Lindley, J.T., 1977. Inputs, outputs and a theory of production and cost at depository financial institution. Journal of Finance 32, 1251-1266.

Servin, R., Lensink, R., van den Berg, M., 2012. Ownership and technical efficiency of microfinance institutions: Empirical evidence from Latin America. Journal of Banking and Finance 36, 2136-2144.

Stiroh, J., Rumble, A., 2006. The dark side of diversification: The case of US financial holding companies. Journal of Banking and Finance 30, 2131 – 2161.

Sun, L., Chang, T-P., 2011. A comprehensive analysis of the effects of risk measures on bank efficiency: Evidence from emerging Asian countries. Journal of Banking and Finance 35, 1727-1735.

Tabak, B.M., Fazio, D.M., Cajueiro, D.O., 2012. The relationship between banking market competition and risk-taking: Do size and capitalization matter? Journal of Banking and Finance 36, 3366-3381.

Tabak, B.M., Fazio, D.M., Cajueiro, D.O., 2013. Systemically important banks and financial stability: The case of Latin America. Journal of Banking and Finance 37, 3855-3866.

Tecles, P.L., Tabak. B.M., 2010. Determinants of bank efficiency: The case of Brazil. European Journal of Operational Research 207, 1587-1598.

Tsionas, E., 2002. Stochastic frontier models with random parameters. Journal of Applied Econometrics 17, 127-147.

Vasconcelos, M.R., Fucidji, J.R., 2002. Foreign entry and efficiency: Evidence from the Brazilian banking industry. Working paper, State University of Maringá.

Williams, J., 2012. Efficiency and market power in Latin American banking. Journal of Financial Stability 8, 263-276.

Yeyati, L., Micco A., 2007 Concentration and foreign penetration in Latin American banking sectors: Impact on competition and risk. Journal of Banking and Finance 31, 1633-1647.

Yildirim, H.S., Philippatos G.C., 2007. Restructuring, consolidation and competition in Latin American banking markets. Journal of Banking and Finance 31, 629-639.

Appendix – Control variables

To mitigate potential endogeneity issues, we construct weighted annual averages of the banking industry descriptors 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:

(1) The ratio of equity-to-assets (ETA) or capitalization that is positively associated with prudence or risk aversion. We expect capitalization is positively related to stability because better capitalized banks are less susceptible to losses arising from unanticipated shocks (Sanya and Wolfe, 2011);

(2) The Z score (Z) is constructed for each bank as Z = RoA+ETA/σ_{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 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 (higher) values of Z imply a higher (lower) probability of bankruptcy (Hannan and Hanweck, 1988; Nash and Sinkey, 1997). We calculate the natural logarithm of Z+100;

(3) It is common to control for differences in the risk appetite of management across banks using ratios such as the stock of loan loss reserves-to-gross loans (LLR) to proxy for asset quality (Mester, 1996). However, this variable is not strictly exogenous if managers are inefficient at portfolio management, or skimp on controlling costs. We use the weighted annual average to proxy the underlying level of risk (Berger and Mester, 1997);

(4) 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 et al., 2006). Income diversification is a proxy for a bank's business model (Fiordelisi et al., 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 ambiguous. It has been suggested diversification may have a negative impact on cost efficiency (Rossi et al., 2009)

(5) The Herfindahl-Hirschman index of assets concentration in each country by year is specified to control for the effects of increases in industry concentration on bank cost. Under the franchise value hypothesis, there is less incentive for banks to assume unnecessary risks in more highly concentrated industries (Keeley, 1990);

(6) The natural logarithm of GDP per capita is proxy for country-level wealth effects;

(7) ΔGDP = annual rate of growth in GDP represents business cycle effects;

(8) The ratio of banking sector credit-to-GDP indicates financial deepening. Levine (2005) suggests a high ratio indicates a strengthening of the corporate governance of banks. Incremental credit provision requires further screening, raising monitoring costs for banks in a manner that could reduce cost efficiency;

(9) The ratio of state-owned bank assets-to-banking sector assets is a proxy for the level of financial repression. State-ownership is reported to result in poorly developed banks (Barth et al., 2001) and reduced cost efficiency (Megginson, 2005). State-owned banks may face a soft budget constraint, which implies that incentives for managers to behave in a cost-minimizing manner are absent (Altunbas et al., 2001). Under-performance of state-owned banks is associated with the level of government involvement, and the perverse incentives of political bureaucrats (Cornett et al., 2010).

Figure 1: Mean Rank Cost Efficiency: by Country

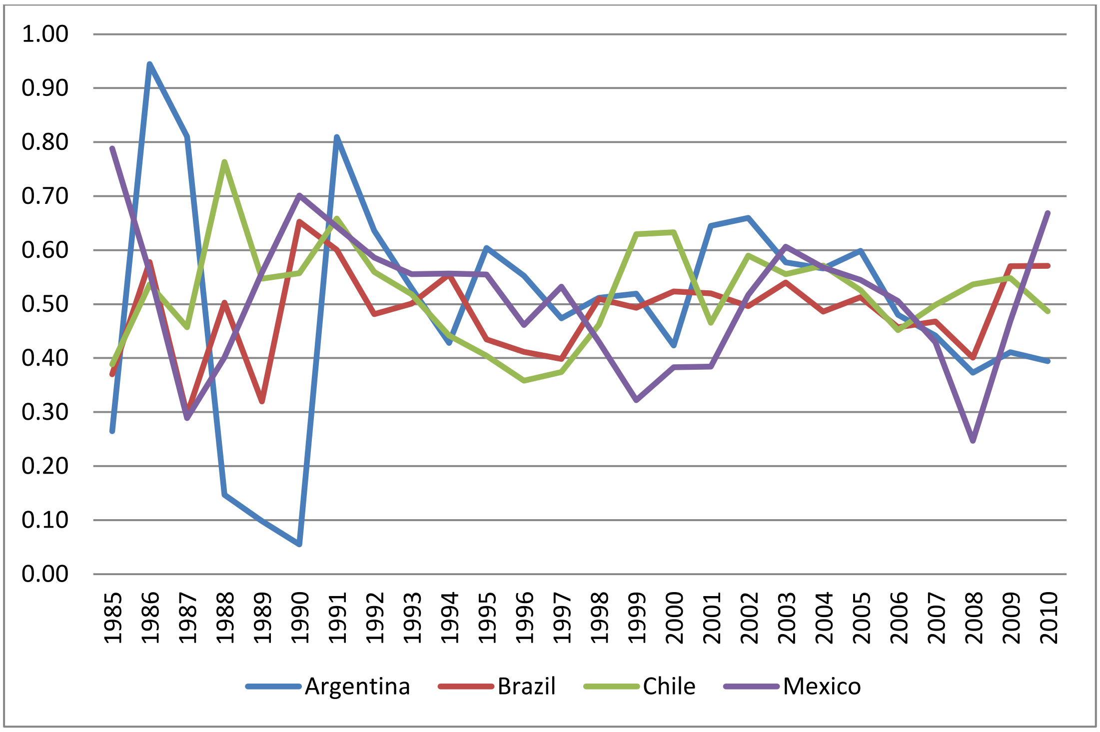
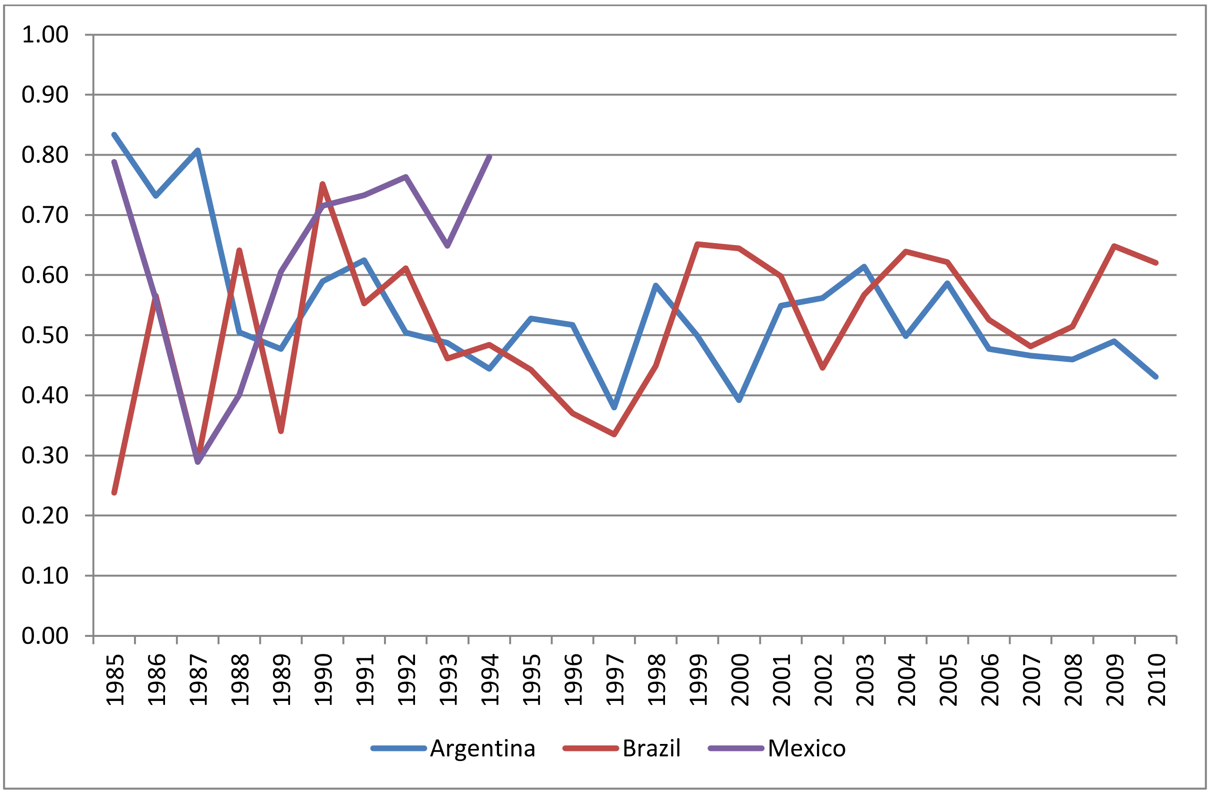


Figure 2: Mean Rank Cost Efficiency of State-owned Banks: by Country



Note: We exclude Chile because the sample contains one state-owned bank. Similarly, the number of state-owned banks in Mexico equals one from 1995 on.

Figure 3: Mean Rank Cost Efficiency of Private-owned Banks: by Country

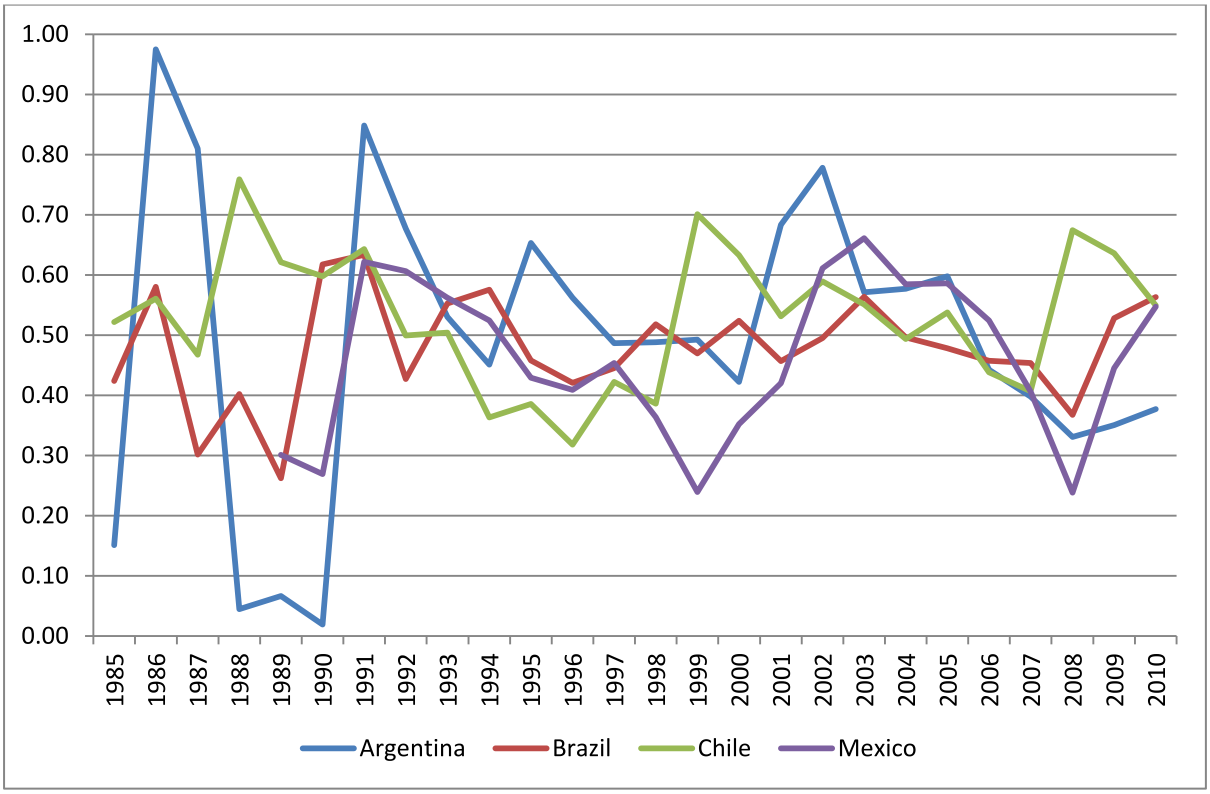
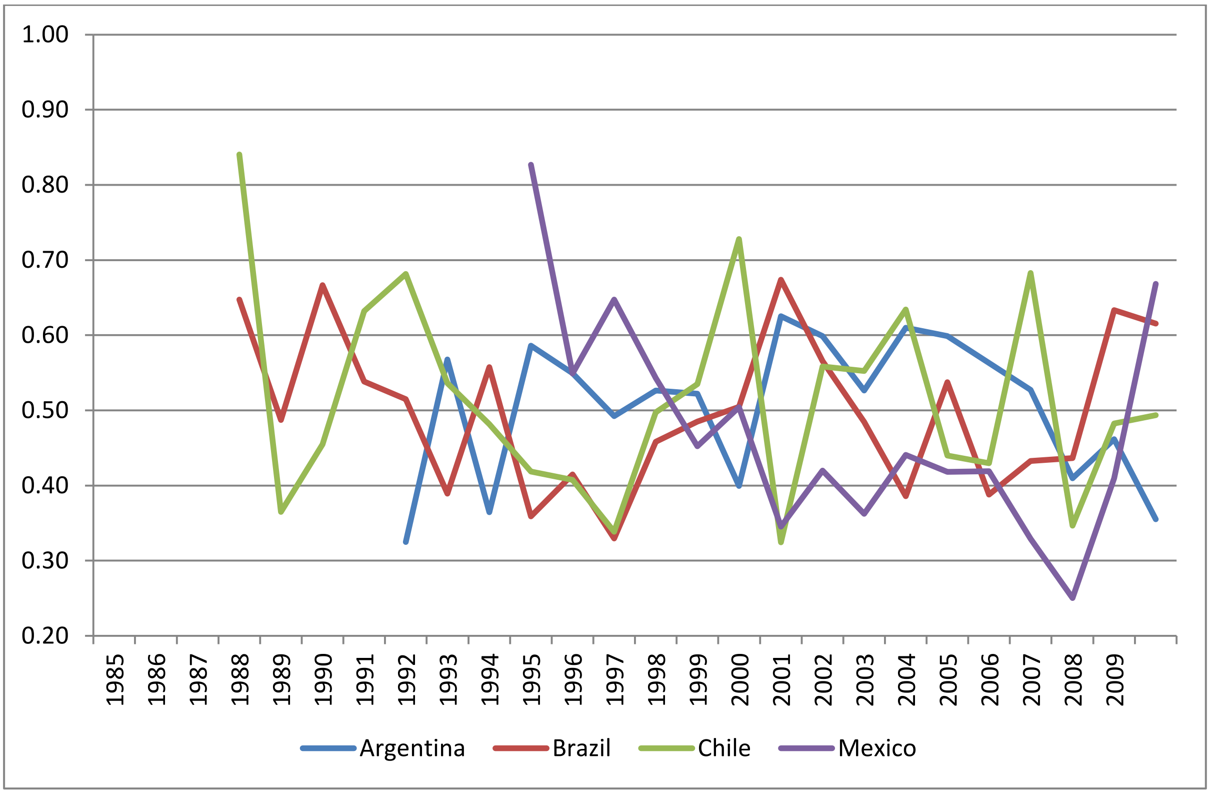


Figure 4: Mean Rank Cost Efficiency of De Novo Foreign Banks: by Country



Note: The start date for each series is determined by there being at least two foreign de novo banks in the sample for each country and year.

Figure 5: Mean Rank Cost Efficiency of Foreign Banks: by Country

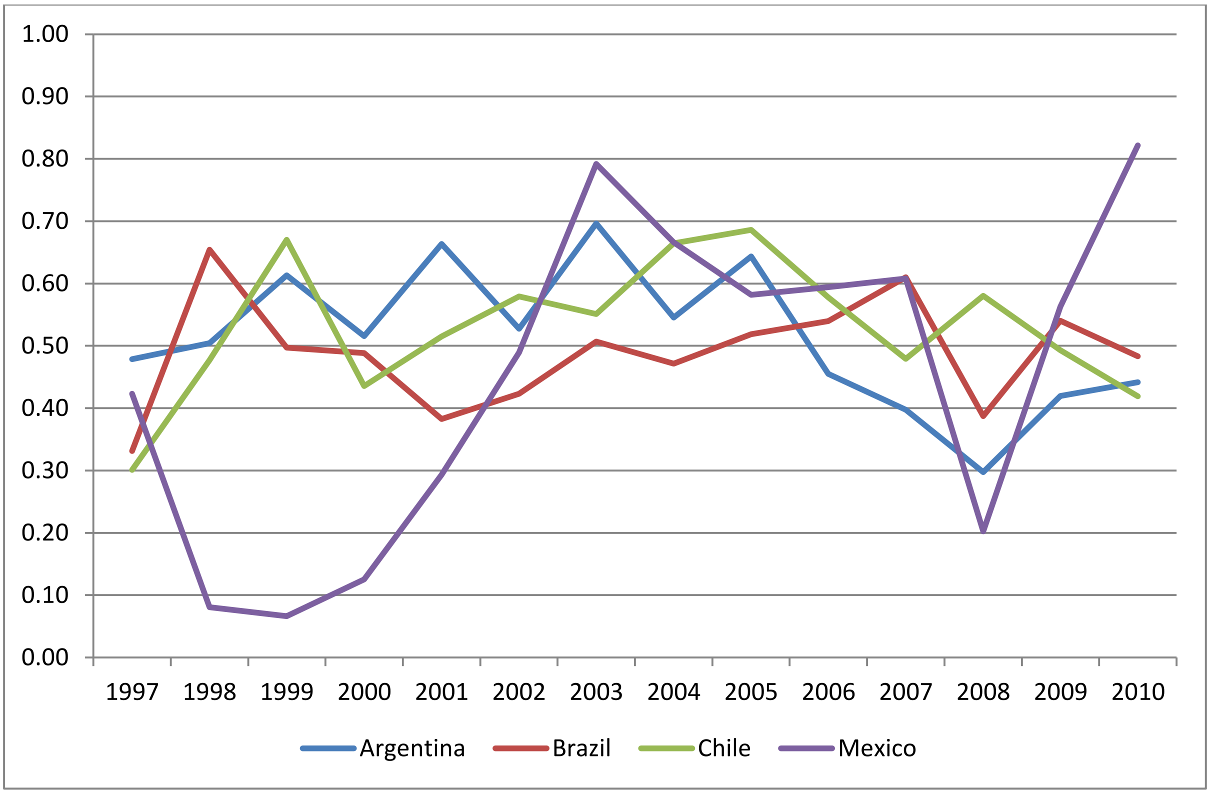


Table 1: Descriptive statistics for the stochastic frontier cost function

Variables[1]	**Mean**	**Stdev**	**Min**	**Max**
Variable cost ($m)	773.3	2,433.8	0.07	59,790.1
Loans ($m)	1,963.9	5,517.8	0.04	83,773.5
Customer deposits ($m)	1,943.1	5,655.3	0.02	83,653.6
Other earning assets ($m)	1,748.8	5,817.4	0.00	85,888.7
Total assets ($m)	4,425.0	13,446.2	2.76	204,730.0
Price of financial capital	0.1777	0.2030	0.0014	1.0789
Price of physical capital	0.8205	0.7816	0.0309	5.0234
Price of labour	0.0304	0.0233	0.0005	0.1222
Equity-to-assets[2]	0.0943	0.0214	0.0333	0.2330
Z score (rolling 4 yrs)[2]	20.028	12.742	3.280	81.144
Herfindahl index	1144.8	770.0	584.3	7591.4
Loan loss reserves-to-loans[2]	0.1263	0.0938	0.0113	0.3628
Diversification index[2,3]	0.3554	0.0748	0.1151	0.4716
GDP per capita ($m)	5,228.1	2,211.9	2,606.4	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

Notes: (1) The data are expressed as ratios unless otherwise indicated; (2) the data are weighted annual averages where the weight is the share of bank *i* in total assets in country *j* at time *t*; (3) the diversification index is calculated for bank income.

Table 2: Correlations between true and estimated inefficiency scores, summary statistics from Monte Carlo simulations

		Correlation between true and estimated efficiency scores			
Data generating process	Estimated Model	Mean	Standard deviation	Minimum	Maximum
Model 3	Model 3	0.3329	0.0174	0.2895	0.3673
Model 3	Model 4	0.3332	0.0175	0.2922	0.3674
Model 4	Model 3	0.1428	0.0169	0.1144	0.1861
Model 4	Model 4	0.1757	0.0157	0.1380	0.2082

Table 3: Estimated parameters from stochastic frontier cost functions; Models 1 – 3

		Model 1 - Standard Cost Frontier	Model 2 - Fixed Effects (FE)	Model 3 - Random Effects (RE)			Model 1 - Standard Cost Frontier	Model 2 - Fixed Effects (FE)	Model 3 - Random Effects (RE)
Var	**Par**	**Coeff.**	**Coeff.**	**Coeff.**	**Var**	**Par**	**Coeff.**	**Coeff.**	**Coeff.**
Cons	A	2.644***	-	-	T	β_{21}	0.019***	-	0.017***
q_{1it}	β_1	0.369***	0.400***	0.341***	T^2	β_{22}	-0.001***	-	-0.001***
q_{2it}	β_2	0.144***	0.044	0.165***	$q_{1it}T$	β_{23}	0.002	0.001	-0.001
q_{3it}	β_3	0.378***	0.415***	0.302***	$q_{2it}T$	β_{24}	0.002	0.003**	0.002**
p_{1it}	β_4	0.381***	0.356***	0.300***	$q_{3it}T$	β_{25}	-0.003***	-0.002***	-0.003***
P_{2it}	β_5	0.258***	0.299***	0.287***	$p_{1it}T$	β_{26}	-0.005***	-0.003***	-0.003***
q_{1it}^2	β_6	0.153***	0.163***	0.137***	$p_{2it}T$	β_{27}	0.003***	0.002*	0.006***
$q_{1it}q_{2it}$	β_7	-0.039***	-0.022***	-0.037***	ETA	ϕ_1	0.464	1.266***	-0.043
$q_{1it}q_{3it}$	β_8	-0.089***	-0.106***	-0.076***	Z	ϕ_2	-0.102**	-0.609***	-0.121**
q_{2it}^2	β_9	0.040***	0.016*	0.050***	HHI	ϕ_3	0.194***	0.186***	0.167***
$q_{2it}q_{3it}$	β_{10}	-0.013***	-0.004	-0.022***	LLR	ϕ_4	0.252**	-0.406***	0.015
q_{3it}^2	β_{11}	0.108***	0.104***	0.115***	DIV	ϕ_5	-0.104	-0.007	-0.052
p_{1it}^2	β_{12}	0.107***	0.090***	0.116***	GDP	ϕ_6	-0.250***	-0.512***	-0.255***
$p_{1it}p_{2it}$	β_{13}	-0.017***	0.005	-0.009***	ΔGDP	ϕ_7	0.004***	0.003**	-0.003***
p_{2it}^2	β_{14}	0.033***	0.018**	0.015***	CR	ϕ_8	-0.103**	-0.395***	-0.054
$q_{1it}p_{1it}$	β_{15}	0.028***	0.039***	0.025***	SO	ϕ_9	0.046	0.114**	-0.105***
$q_{1it}p_{2it}$	β_{16}	-0.046***	-0.073***	-0.035***		$\bar{\alpha}$		-	3.536***
$q_{2it}p_{1it}$	β_{17}	0.001	-0.024***	0.010***	$\lambda = (\sigma_u/\sigma_v)$		2.721***	3.329***	0.788***
$q_{2it}p_{2it}$	β_{18}	0.003	0.027***	-0.012***	Σ		0.466***	1.196***	0.290***
$q_{3it}p_{1it}$	β_{19}	0.003	0.027***	-0.012***	σ_v		0.161	0.344	0.228
$q_{3it}p_{2it}$	β_{20}	0.007**	0.011**	0.013***	σ_u		0.437	1.146	0.179

Notes: See pages 10-11 for model definition. For brevity, we report estimated parameters only. Unabridged tables containing the standard errors are available from the authors.
***, **, * indicate significance at the 1, 5 and 10 per cent levels.

Table 4: Estimated parameters from stochastic frontier cost functions; Models 4 – 6

	Model 4		**Model 5**			**Model 6**			**Model 4**		**Model 5**			**Model 6**	
	α_i, β_{ji}	$\sigma(\alpha_i)$, $\sigma(\beta_{ji})$	α_i or β_{ji}	δ_j	$\sigma(\alpha_i\|s_i)$, $\sigma(\beta_{ji}\|s_i)$	α_i, β_{ji}	$\sigma(\alpha_i)$, $\sigma(\beta_{ji})$		β_{ji}, ϕ_j	$\sigma(\beta_{ji})$	β_{ji}, ϕ_j	δ_j	$\sigma(\beta_{ji}\|s_i)$	β_{ji}, ϕ_j	$\sigma(\beta_{ji})$
const	5.8707**	0.0771**	4.1816**	-0.0312	0.1819**	4.6364**	0.1406**	T	0.0200**	0.0096**	0.0119	0.0003	0.0010**	0.0075	0.0097**
q_{1it}	0.3016**	0.0257**	0.1261	0.0227*	0.0065**	0.2954**	0.0023**	T^2	-0.0000	0.0003**	0.0005	-0.0001	0.0002**	0.0000	0.0000**
q_{2it}	0.1703**	0.0165**	0.0177	0.0182	0.0109**	0.1807**	0.0006	$q_{1it}T$	-0.0014	0.0002**	-0.0090**	0.0012*	0.0001*	-0.0009	0.0002**
q_{3it}	0.3035**	0.0050**	0.2961**	-0.0053	0.0018**	0.3368**	0.0039**	$q_{2it}T$	0.0011**	0.0014**	0.0112**	-0.0016**	0.0009**	0.0023**	0.0004**
p_{1it}	0.2559**	0.0401**	0.1390*	0.0193*	0.0297*	0.3185**	0.1075**	$q_{3it}T$	-0.0026**	0.0000	-0.0069**	0.0008**	0.0039**	-0.0038**	0.0044**
p_{1it}	0.3382**	0.0381**	0.3242**	-0.0089	0.0333**	0.2574**	0.0069**	$p_{1it}T$	-0.0037**	0.0076**	0.0003	-0.0005	0.0008**	-0.0051**	0.0026**
q_{1it}^2	0.1434**	0.0036**	0.2184**	-0.0104**	0.0021**	0.1427**	0.0014**	$p_{2it}T$	0.0030**	0.0010**	-0.0012	0.0004	0.0096**	0.0048**	0.0085**
$q_{1it}q_{2it}$	-0.0425**	0.0000	-0.1111**	0.0118**	0.0002**	-0.0387**	0.0007**	ETA	-1.0555**	-	-0.7087**	-	-	0.0988	-
$q_{1it}q_{3it}$	-0.0705**	0.0020**	-0.0604**	-0.0016	0.0005**	-0.0777**	0.0018**	Z	-0.0127	-	-0.1014*	-	-	-0.0422	-
q_{2it}^2	0.0521**	0.0082**	0.0926**	-0.0069*	0.0023**	0.0535**	0.0009**	HHI	0.0748**	-	0.0970**	-	-	0.0603**	-
$q_{2it}q_{3it}$	-0.0283**	0.0043**	-0.0160	-0.0015	0.0030**	-0.0315**	0.0005**	LLR	0.0279	-	0.0038	-	-	0.0770	-
q_{3it}^2	0.1179**	0.0062**	0.1787**	-0.0097**	0.0020**	0.1228**	0.0009**	DIV	0.0873	-	-0.0666	-	-	-0.0015	-
p_{1it}^2	0.1256**	0.0102**	0.0917**	0.00272	0.0494**	0.1265**	0.0807**	GDP	-0.5410**	-	-0.2230**	-	-	-0.3589**	-
$p_{1it}p_{2it}$	-0.0217**	0.0196**	-0.0131	0.0000	0.0157**	-0.0166**	0.0010**	ΔGDP	-0.0012	-	-0.0025**	-	-	-0.0017*	-
p_{2it}^2	0.0206**	0.0034**	-0.0118	0.0074**	0.0040**	0.0107**	0.0052**	CR	0.0325	-	0.0237	-	-	0.04722	-
$q_{1it}p_{1it}$	0.0290**	0.0011**	-0.0792**	0.0171**	0.0140**	0.0174**	0.0114**	SO	0.1077**	-	-0.1014**	-	-	0.0146	-
$q_{1it}p_{2it}$	0.0196**	0.0034**	0.1995**	-0.0272**	0.0029**	0.0197**	0.0012**	$\bar{\theta}$	-	-	-	-	-	0.8017**	-
$q_{2it}p_{1it}$	-0.0037*	0.0154**	-0.0393**	0.0036*	0.0158**	-0.0067**	0.0110**	δ_θ	-	-	-	-	-	-0.0896**	-
$q_{2it}p_{2it}$	-0.0318**	0.0047**	0.1180**	-0.0258**	0.0018**	-0.0196**	0.0011**	λ	1.4141**	-	1.3909**	-	-	1.2856	-
$q_{3it}p_{1it}$	0.0068*	0.0015**	-0.0336*	0.0065**	0.0026**	-0.0071**	0.0014**	σ	0.2630**	-	0.2586**	-	-	-	-
$p_{3it}q_{2it}$	-0.0019	0.0128**	-0.0957**	0.0176**	0.0052**	0.0081**	0.0020**	σ_v	0.1519	-	0.1510	-	-	0.1548	-
-	-	-	-	-	-	-	-	σ_u	0.2147	-	0.2100	-	-	0.1990	-

Notes: For Models 4, 5 and 6, the 'Intcpt' column reports $\bar{\alpha}$, $\bar{\beta}_j$ for j=1,...,27, and ϕ_j for j=1,...,9. For Models 4 and 6, the 'S.D.' column reports $\sigma(\alpha_i)$, and $\sigma(\beta_{ji})$ for j=1,...,27. For Model 5, the 'Slope' column reports δ_j for j=1,...,27. The 'S.D.' column reports $\sigma(\alpha_i|s_i)$, and $\sigma(\beta_{ji}|s_i)$ for j=1,...,27. *, ** indicate statistical significance at 1 and 5 percent.

Table 5: Descriptive statistics: variable cost efficiency by model (u_{it} ~ half normal)

Model	Mean	Stdev	Min	Max	Skew.	Kurt.
Standard panel, Model 1	0.7441	0.1172	0.4108	0.9760	-0.936	3.756
Fixed effects, Model 2	0.5577	0.0928	0.0579	0.9412	-1.046	6.719
Random effects, Model 3	0.8696	0.0395	0.3734	0.9776	-4.094	34.783
Random parameters, Model 4	0.8526	0.0627	0.2137	0.9802	-3.668	25.726
RPM heterogeneity, Model 5	0.8547	0.0611	0.2344	0.9805	-3.510	25.200
RPM heterogeneity, Model 6	0.8300	0.0802	0.2281	0.9860	-1.950	9.690

Table 6: Spearman rank order correlations of variable cost efficiency[1]

Model	Model 1	Model 2	Model 3	Model 4	Model 5
Fixed effects, Model 2	0.6400				
Random effects, Model 3	0.6891	0.8150			
Random parameters, Model 4	0.5626	0.6772	0.7984		
RPM heterogeneity, Model 5	0.5531	0.6593	0.7862	0.8299	
RPM heterogeneity, Model 6	0.8262	0.4917	0.5793	0.4801	0.4777

Note: (1) All parameters are significant at the 1 per cent level