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Abstract

This paper presents a stochastic frontier model with random inefficiency parameters which captures the influence of risk-taking on bank efficiency and distinguishes the effects among banks with different characteristics. The model is fitted to a 10-year sample of Colombian banks. Cost and profit efficiency are found to be over and underestimated, respectively, when risk measures are omitted or are not accurately modelled. Moreover, the magnitudes at which similar levels of risk affect bank efficiency vary with size and affiliation. In particular, domestic and small Colombian banks benefit more from being highly capitalised, while large and foreign banks benefit from higher exposure to credit and market risk. Holding more liquid assets is found to affect efficiency only at domestic banks. Lastly, we identify some channels that can explain these differences and provide insights for prudential regulation.

Keywords: bank efficiency, Bayesian inference, heterogeneity, random parameters, risk-taking, stochastic frontier models.

JEL classification: C11, C23, C51, D24, G21, G32.

Resumen

Este trabajo presenta un modelo de frontera estocástica con parámetros aleatorios en el componente de ineficiencia aplicado al sector bancario. Este modelo permite capturar la influencia de las exposiciones de riesgo sobre la eficiencia bancaria y distingue estos efectos entre bancos con diferentes características. El modelo es ajustado a una muestra de 10 años de bancos colombianos. Se encuentra que, cuando las medidas de riesgo son omitidas o no son modeladas adecuadamente, las estimaciones de eficiencia en costos y en beneficios son sobreestimadas y subestimadas, respectivamente. Adicionalmente, las magnitudes en las cuales niveles similares de riesgo afectan la eficiencia bancaria varían de acuerdo con el tamaño y el tipo de propiedad de los bancos. En particular, los bancos pequeños y nacionales se benefician más de altos niveles de capitalización, mientras que los bancos grandes y extranjeros se benefician de mayores exposiciones de riesgo de crédito y de mercado. También se encuentra que una mayor tenencia de liquidez tiene efectos únicamente sobre la eficiencia de los bancos nacionales. Finalmente, se identifican los canales que pueden explicar esas diferencias y algunas ideas de regulación prudencial.

Palabras clave: eficiencia bancaria, inferencia bayesiana, heterogeneidad, parámetros aleatorios, toma de riesgo, modelos de frontera estocástica.

Códigos JEL: C11, C23, C51, D24, G21, G32.

1. Introduction

The modern banking theory shows that banks' behavior is subject to uncertainty derived from the behavior of borrowers, depositors and financial markets in which banks interact. This type of uncertainty is commonly referred as bank risk-taking. That is, the amount of risk that banks are willing to tolerate, which depends on competition, regulation and corporate governance (Boyd and De Nicoló, 2005; Laeven and Levine, 2009; Wagner, 2010; Agoraki et al., 2011; Anginer et al., 2013). In their pursuit of better performance banks tend to engage in more risk-taking. However, excessive risk-taking lead the financial system to be highly vulnerable to shocks (Rajan, 2006). During the global financial crisis of 2007-08 excessive bank risk-taking was associated with banking runs, fire-sales, and financial fragility (Brunnermeier and Pedersen, 2009; Shleifer and Vishny, 2010). In response to this behavior, banking regulators have imposed higher capital and liquidity requirements, leverage ratios, and countercyclical provisions for loan losses, among other regulatory measures (see Basel III standards in BIS, 2010, 2011). These measures are intended to discourage risk-taking by imposing higher costs to banks from assuming more risk. Thus, understanding how risk-taking and regulation influences bank performance is an important concern.

In the banking literature recent studies have addressed these effects using different approaches. Several studies accounting for regulatory effects have found that stringency of capital regulation is associated with higher bank efficiency, while limiting banking activities discourages efficiency (Chortareas et al., 2012; Barth et al., 2013; Berger and Bowman, 2013). Other studies have focused on identifying the relationship between credit risk, capitalization and bank efficiency (see the seminal work of Berger and DeYoung, 1997). Most of studies exploring these relationships have found that highly capitalized banks are more cost efficient than banks with low capitalization levels (Williams, 2004; Altunbas et al., 2007; Lepetit et al., 2008; Fiordelisi et al., 2011). Furthermore, banks with low cost efficiency have been found to exhibit higher proportions of bad loans and to be more prone to default (see Podpiera and Weill, 2008; Tabak et al., 2011, for some evidence from emerging economies).

From the structural approach, risk-taking has been identified as a crucial element of the banking production process which should be properly modeled into efficiency measurement (Hughes et al., 2001). Recent studies under this approach show that failure to account for risk-taking may lead to biased estimations of bank efficiency and misleading estimates of scale economies and cost elasticities (Hughes and Mester, 2013; Koetter, 2008; Malikov et al., 2014).

Another widely used approach in the literature is to incorporate risk measures into frontier efficiency methods such as stochastic frontier analysis (SFA). However, most of studies modeling the effects of risk on efficiency under this approach incorporate only proxies for credit risk (usually nonperforming loans) and omit other important risks faced by banks (e.g. liquidity, market or insolvency risk). Some recent studies have accounted for alternative risk measures as inefficiency determinants. Radić et al. (2012) find capital and liquidity risk to have relevant effects on cost and profit efficiency of investment banks in G-7 countries. Also, Pessarossi and Weill (2015) find that a higher capital ratio had a positive influence on cost efficiency of Chinese banks during 2004-2009, suggesting that capital buffers may improve cost efficiency. These studies reveal that accounting for risk-exposure heterogeneity across banks is relevant when measuring bank efficiency. Moreover, the omission of heterogeneity related to size and type of ownership has been identified as an important source of biases in the estimations of banks inefficiency (Bos et al., 2009; Feng and Zhang, 2012; Goddard et al., 2014).

Identifying inefficiency determinants and accounting for heterogeneity is particularly important in the Colombian banking sector given the rapid expansion of the sector in recent years, the important role of foreign institutions and the several mergers and acquisition (M&A) processes that have been carried out. These characteristics have increased the differences in terms of size and capital structure across institutions, which could affect banks' risk-taking behavior and performance. Furthermore, since 2002 several regulatory measures have been implemented by the Colombian regulators in order to enhance loan loss provisions, and to set adequate capital and liquidity requirements to limit risk-taking. These measures were initially motivated by a profound financial crisis at the end of 1990s that evidenced the vulnerability of the Colombian banking sector to external shocks. Previous studies, although failing to control by risk, have found gains in efficiency of Colombian banks in recent years and have identified that large and foreign banks are more efficient than their counterparts. In this context, recognizing differences in the way risk exposures affect different types of banks becomes relevant in order to get more accurate efficiency estimations and a complete understanding of the effects of risk and macroprudential regulation on bank performance.

The aim of this paper is to identify the influence of risk-taking on cost and profit efficiency of banks and to differentiate these effects between banks with different sizes and affiliations. We contribute to the literature by proposing a stochastic frontier model with random inefficiency coefficients, which allows us to identify the influence of unobserved heterogeneity sources related to risk-taking on bank efficiency. Our approach is close to that in Feng and Zhang (2012); Goddard et al. (2014) in which random parameters are used in order to account for unobserved bank heterogeneity. However, in our model random parameters are modeled in the inefficiency component rather than in the frontier. This allows us to estimate consistently in a single step heterogeneous effects of risk-exposure measures on bank inefficiency. In particular, we account for the influence of capital, liquidity, credit, and market risk exposures on cost and profit efficiency and distinguish these effects by types of banks. The inference of the model is carried out via Bayesian methods that formally incorporate parameter uncertainty and allows deriving bank-specific distributions of efficiency and risk random coefficients. The model is estimated for the Colombian banking sector using bank-level data from 2002 to 2012. This period covers several regulatory measures that were implemented to limit bank risk-taking and to promote the foreign entry of banks. The period considered also allows us to assess the effects of the global financial crisis on the efficiency of Colombian banks.

In line with recent evidence, our findings remark the importance of accounting for size, affiliation and risk exposure in the estimation of bank efficiency. We find that cost and profit efficiency are over- underestimated when risk measures are not accurately modeled (see Hughes et al., 2001; Koetter, 2008; Radić et al., 2012, for similar results). Furthermore, we identify that size and foreign ownership are not only important determinants of efficiency but also key characteristics defining the way credit and market risk, liquidity and capitalization levels affect cost and profit efficiency. Domestic and small Colombian banks benefit more from being highly capitalized, while large and foreign banks from engaging in higher credit and market risk. We find that large Colombian banks exhibit higher efficiency than small institutions and that foreign and small banks were more affected by the financial crisis and the regulatory measures introduced after 2008. We explain the main channels supporting these differences in efficiency among banks with different characteristics.

2. The Colombian banking sector: performance and regulation

During early 1990s the Colombian banking sector was gradually introduced into the global economy by a financial liberalization program following the trend of other Latin-American economies (Carvalho et al., 2014). The program eased restrictions for foreign participation in the banking sector, established a kind of universal banking scheme intended to reduce specialization, and implemented financial regulatory measures to promote competition and efficiency in the financial sector.[1] As a result, by 1997 most of state-owned banks were privatized. The share of public banks in the total assets of the financial system dropped from 43% to 13%, the number of financial institutions increased from 91 in 1990 to 155 in 1997 and the ratio of credit to GDP increased from 30% to 44% (Uribe and Vargas, 2002).

[1]Colombian banks are not allowed to offer some financial services that are included in the standard universal banking approach such as insurance and trust activities.

Evidence has shown that the financial liberalization process in Colombia had positive consequences by increasing competition and efficiency, lowering intermediation costs and improving loan quality. However, after some years the greater competition with foreign banks resulted in higher risk levels and a subsequent deterioration of loans quality, especially among domestic banks (Barajas et al., 2002). In 1999 the Colombian banking sector was affected by local and external shocks that triggered the financial conditions in the sector and lead to a profound financial crisis. The external shock from the Asian financial crisis led to capital outflows and a rapid depreciation of the exchange rate. At local level, an economic downturn, and the raise of real interest rates forced to a rapid deterioration of loan quality that eroded the solvency of the sector. Previous studies reveal that this rapid deterioration of the financial sector was mainly a consequence of low loan loss provisions and low capitalization levels (Gomez-Gonzalez, 2009). Between 1998 and 2001 several banking institutions failed, and other were merged. Institutions specialized in mortgage loans were absorbed by large commercial banks. In consequence, the number of banking institutions felt from 100 in 1998 to 57 in 2001; while the annual rate of credit growth declined from 30% to -6% during the same period.

Following the financial crisis, Colombian financial authorities strengthened the regulatory measures intended to enhance adequate provisions for loan losses, and higher capital and liquidity ratios. These regulatory measures were designed under the Basel standards with the aim of accounting for the interaction of credit risk with liquidity and market risk.

Since 2002, risky loans (based on internal loans ratings) were designated as the target measure to set banks provisions for loan losses, rather than the traditional non-performing loans (NPL). Thus, loan provisions were settled on an ex-ante measure of credit risk instead of being computed using an ex-post measure of credit risk (i.e NPL).[2] Market risk was defined as an estimated value by each bank using the Value at Risk (VaR) of its securities portfolio, which was included as an additional component in the capital ratio since 2008. Hence, the higher the market exposure the larger the required capital for the solvency ratio.[3] New definitions of equity capital were also implemented to enhance quality of capital (Tier 1 and Tier 2). Finally, a short-run liquidity ratio (LR) was required for banks to hedge from liquidity mismatches.[4]

[2]Provisions vary according to borrowers rating from 1% for type A borrowers up to 20% for type E borrowers.

[3]Capital ratio (CR) should be greater than 9% and is defined as equity capital (CE) over risky weighted assets (RWA) plus 100/9 of the (VaR). Formally, $CR = CE/[RWA + (100/9)(VaR)]$, where $CR > 9\%$.

[4]LR is the value of liquid assets over short-term liabilities. LR should be positive for maturities of 7 and 30 days, although it can be negative for 14 days maturities in order to account for the reserve requirement that banks have to fulfill every two weeks. Previous to LR, regulators used a ratio of liquid assets over volatile liabilities.

Overall, the above-mentioned regulatory measures have served to influence banks behavior due to the incorporation of risk-taking. These measures along with other macroprudential policies implemented in 2006-07 played an important role to avoid the contagion from the global financial crisis of 2007-08.[5] Nevertheless, as we show further, an important decrease in both cost and profit efficiency was observed during that period, especially for small and foreign banks.

During the period 2002-2012 the Colombian banking sector experienced a growing expansion that has been accompanied by the arrival of foreign banks. The aggregated value of loans grew 300% and the investments to assets ratio doubled. Banks increased their competition in the securities market with non-banking institutions (i.e. Brokerage firms) and also boosted their participation in the money market for short-term liquidity. Several M&A processes were also carried out, concentrating financial services in a few but large institutions. As a result, risk exposures presented important increases.[6] This has required the regulator to closely monitor credit and market risk and to face the challenges of systemic financial institutions (see León et al., 2012).

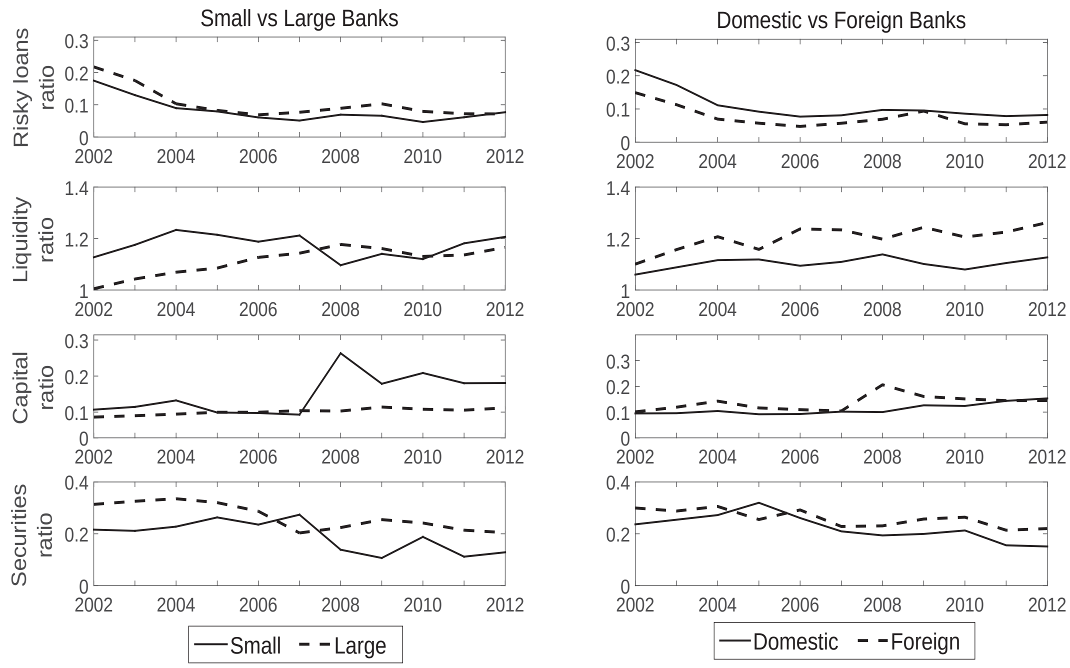
Figure 1 shows the evolution of ratios related to credit, liquidity, capital and market risk over the period 2002-2012 by distinguishing between small and large banks and foreign and domestic banks.[7] In general, Colombian banks exhibit a downward trend in credit and market risk along with stable levels of capitalization and growing liquidity. However, important differences in the level of risk exposure of banks with different characteristics of size and ownership are observed, which coincide with the aforementioned regulatory changes including those adopted in 2007-08 to meet Basel II standards. We observe that the ratio of risky loans over total loans has declined for all banks although large and domestic banks exhibit higher levels than small and foreign banks. This decreasing trend even during a period of large credit expansion and high economic growth may be related with the introduction of the use of risky loans as an indicator for loan losses provisions in 2002. The ratio of liquid assets over total assets has gradually increased over time, especially for large and foreign banks. Capital ratio seems to be stable for large

[5]The government settled limits to banks positions in foreign currency and extended to two years the period for allowing foreign capital outflows.

[6]In May 2013, Colombian Treasury Bill (TES) prices decreased 20% in two weeks as a result of the uncertainty related to FED's exit strategy. This led to bank losses of COP 2.32 billion that represented 4.87% of their equity capital.

[7]We define small and large banks as those below and above the median of the total assets level, respectively.

Figure 1: Evolution of risk-exposure measures by type of bank 2002 - 2012



banks in Colombia while important increases are observed for small and foreign banks from 2008. Likewise, small banks reduced more than large institutions their holdings of securities after the global financial crisis. This may suggest that small banks were more concerned about the effects of exposures in credit and securities markets due to the lower probability of being saved given their size, which made them to highly increase their capital ratios and diminish their market risk exposures (see Berger and Bowman, 2013, for similar findings in the US banking sector).

2.1. Efficiency of the Colombian Banking Sector

Early studies of banking efficiency have found evidence of low cost efficiency in the Colombian banking sector during the 90's although some improvements during the first half of 2000s in merged banks (Estrada and Osorio, 2004; Clavijo et al., 2006). Recent studies have provided evidence on improvements in technical efficiency and productivity in the sector but large heterogeneity among banks. Sarmiento et al. (2013), using a non-parametric frontier model, found that Colombian banks improved in technical efficiency from 2000 up to the global financial crisis of 2007-08, when efficiency and productivity decreased. They also found M&A to have a significant and positive impact on bank efficiency, and high heterogeneity in efficiency irrespective of banks' size and affiliation. Galán et al. (2015) estimated input-oriented technical efficiency during the period 2000-2009 using a dynamic Bayesian SFA model. They found out that foreign ownership has positive and persistent effects on efficiency of Colombian banks, while the effects of size are positive but rapidly adjusted. They also identified high inefficiency persistence and important differences between institutions. In particular, merged banks were found to exhibit low costs of adjustment that allowed them to rapidly recover the efficiency losses derived from merging processes.

Finally, Moreno and Estrada (2013) studied the role of market power in explaining efficiency gains in Colombian banks during the 2004-2012 period. By using SFA and non-parametric models, they found a positive relationship between market power and efficiency, which is explained by product differentiation that allows banks to gain efficiency while not charging excessive credit prices. However, previous applications have not studied the influence of risk-taking on efficiency of Colombian banks.

3. Methodology

Frontier efficiency methods have become a very important tool to identify relevant bank inefficiency drivers and to provide useful indicators of performance of the sector and individual institutions. In particular, SFA, firstly introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), presents the advantages of allowing inferences on the parameters, accounting for idiosyncratic errors and modeling firm characteristics that affect directly the inefficiency in a single stage.[8] In this context, bank characteristics related to their risk exposures can be easily and consistently accounted for in cost and profit efficiency estimations.

3.1. Heterogeneity and Risk in Bank Efficiency Measurement

Distinguishing inefficiency from heterogeneity is an important issue in the efficiency frontier literature. Omitting heterogeneity variables has been identified to lead to biased estimations of inefficiency (see Greene, 2005). In the banking literature, Bos et al. (2009) identify these effects on efficiency levels and rankings when observed heterogeneity is omitted. In particular, in the case of risk exposure, Radić et al. (2012) evaluate a sample of 800 investment banks of G-7 countries during the period 2001-2007 and find that omitting bank risk-taking from efficiency estimations leads to underestimating profit efficiency. The authors also find liquidity and capital risk exposures to be the most relevant factors determining cost and profit inefficiency.

[8] In contrast, the main nonparametric method of Data Envelopment Analysis is more flexible but provides, in general, deterministic measures for inefficiency and does not allow accounting for inefficiency heterogeneity in a consistent single stage.

Unobserved heterogeneity has also been found to affect estimations from stochastic frontier models.[9] In applications to the banking sector, Feng and Zhang (2012) find that failure to consider unobserved heterogeneity results in misleading efficiency rankings and mismeasured technical efficiencies, productivity growth, and returns to scale. Goddard et al. (2014) compare different fixed effects, random effects and random parameters models in an application to Latin American banks between 1985 and 2010. They find that random parameters models perform better in distinguishing heterogeneity from inefficiency as well as important differences on cost efficiency estimations. Williams (2012) applies a random parameters model in order to test the quiet life hypothesis in Latin American banks. However, the fact that the author estimates a second stage where cost efficiency is regressed on a market power index and other bank characteristics may lead to biased and inconsistent efficiency estimations (see Wang and Schmidt, 2002).

In this context, our proposal is intended to model unobserved heterogeneity sources related to risk exposures and to account for bank characteristics in a single stage. Our approach is close to that in Goddard et al. (2014); Williams (2012) in the use of random parameters in the inefficiency component. However, we propose to estimate as random the coefficients associated to the observed covariates in the inefficiency distribution. This allows us to obtain in a single stage bank-specific estimates of the effects of risk-exposure measures on cost and profit inefficiency. This specification is more flexible than imposing interactions of observed covariates with different groups of banks.

3.2. A Stochastic Frontier Model with Random Inefficiency Coefficients

Since we are interested in identifying unobserved heterogeneity related to the effects of risk on bank inefficiency, we propose a stochastic frontier model where the coefficients of risk-exposure measures in the inefficiency distribution are modeled as bank-specific parameters. The proposed specification is the following:

$$\begin{aligned} y_{it} = \quad & \mathbf{x_{it}}\boldsymbol{\beta} + v_{it} - u_{it} \\ & v_{it} \sim N(0, \sigma_v^2) \\ & u_{it} \sim Exp(\lambda_{it}) \\ & \lambda_{it} = exp(z_{it}\boldsymbol{\gamma} + z_{it}^{*}\boldsymbol{\gamma}_i^{*}), \end{aligned} \tag{1}$$

where y_{it} represents the output for firm i at time t, $\mathbf{x}_{it}$ is a row vector that contains the input quantities, $\boldsymbol{\beta}$ is a vector of parameters, v_{it} is an idiosyncratic error

[9] Greene (2005) proposes different methods to deal with this kind of heterogeneity under the frequentist approach. In the Bayesian context, Galán et al. (2014) propose the inclusion of a random parameter in the inefficiency component that can be modeled along with other observed covariates and performs well in capturing latent heterogeneity.

assumed to follow a normal distribution, and u_{it} is the inefficiency component. The inefficiency is assumed to follow an exponential distribution with a firm specific and time-varying parameter λ_{it}, $\boldsymbol{\gamma}$ is a vector of parameters which are common to all firms, including the constant, and $\boldsymbol{\gamma}_i^*$ is a vector of firm-specific parameters intended to capture differences in the effects of covariates across firms on the inefficiency. Therefore, $\mathbf{z}_{it}$ is a vector of heterogeneity variables whose effects are assumed to be constant across firms, and $\mathbf{z}_{it}^*$ contains a set of heterogeneity variables with bank-specific effects.

This specification with random coefficients in the parameter of the inefficiency distribution is flexible in the sense that some covariates can be associated with firm specific coefficients while other heterogeneity variables may be modeled with fixed coefficients. In particular, the random coefficients are intended to capture differences in the way risk exposures affect efficiency of different types of banks. Thus, the model is able to identify not only the effects of risk on inefficiency but also the type of banks that are more affected by each of the risk-exposure measures.

3.3. Bayesian Inference

The inference of the model is carried out using Bayesian methods. This approach was introduced in stochastic frontier models by van den Broeck et al. (1994) and allows us to formally incorporate parameter uncertainty and derive posterior densities of cost and profit efficiency for every individual bank.

We assume proper but relatively dispersed prior distributions throughout. In particular, the distributions assumed for the parameters in the frontier are: $\boldsymbol{\beta} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\beta}})$ where $\boldsymbol{\Sigma}_{\boldsymbol{\beta}}^{-1}$ is a precision diagonal matrix with priors set to 0.001 for all coefficients. The variance of the idiosyncratic error term is inverse gamma, which is equivalent to $\sigma_v^{-2} \sim G(a_{\sigma_v^{-2}}, b_{\sigma_v^{-2}})$ with priors set to 0.01 for the shape and rate parameters, respectively.

Regarding the inefficiency component, its distribution is assumed to be exponential: $u_{it}|\boldsymbol{\gamma}, \boldsymbol{\gamma}^*, \mathbf{z_{it}}, \mathbf{z_{it}^*} \sim Exp(\exp(\mathbf{z_{it}}\boldsymbol{\gamma} + \mathbf{z_{it}^*}\boldsymbol{\gamma}_i^*))$. The prior distribution of the vector of common parameters is $\boldsymbol{\gamma} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\gamma}})$ with priors for the diagonal precision matrix $\boldsymbol{\Sigma}_{\boldsymbol{\gamma}}^{-1}$ equal to 0.1 for all the coefficients. For the firm-specific inefficiency heterogeneity coefficients, a hierarchical structure is defined, where $\boldsymbol{\gamma}_i^* \sim N(\boldsymbol{\gamma}^*, \boldsymbol{\Sigma}_{\boldsymbol{\gamma}^*})$ and $\boldsymbol{\gamma}^*$ is defined in the same way as $\boldsymbol{\gamma}$. Sensitivity analysis is performed to the use of an exponential prior distribution for the inefficiency parameters. In this case they are chosen to be centered in a given prior mean efficiency value r^* following the procedure in Griffin and Steel (2007), where $\exp(\boldsymbol{\gamma}) \sim Exp(-\ln r^*)$.[10] Results show convergence to roughly the same values after the number of iterations described below.

[10] r^* is set at 0.65, following other Bayesian SFA studies in banking (see Tabak and Tecles, 2010).

Markov Chain Monte Carlo (MCMC) methods and in particular the Gibbs Sampling algorithm with data augmentation, as presented by Koop et al. (1995) for stochastic frontier models, can be used here.[11] The MCMC algorithm involves 50,000 iterations where the first 10,000 are discarded and a thinning equal to 4 is used to remove autocorrelations. Therefore, 10,000 iterations are used for the posterior inference.

We assess the fit and predictive performance of the different models using a version of the Deviance Information Criterion (DIC) called DIC_3 and the Log Predictive Score (LPS) (see Griffin and Steel, 2004; Galán et al., 2014, for applications of these criteria to Bayesian SFA models). The former is a stable variant of the within sample measure of fit introduced by Spiegelhalter et al. (2002) commonly used in Bayesian analysis. Defining the deviance of a model with parameters θ as $D(\theta) = -2\log f(\mathbf{y}|\theta)$, where $\mathbf{y}$ is the data, then $DIC = 2\overline{D(\theta)} - D(\bar{\theta})$. However, using an estimator of the density $f(\mathbf{y}|\theta)$ instead of the posterior mean $\bar{\theta}$ is more stable. This alternative specification presented by Celeux et al. (2006) overcomes robustness problems when the original DIC is implemented to random effects and mixture models. The formulation for this criterion is:

$$DIC_3 = -4E_\theta[\log f(\mathbf{y}|\theta)|\mathbf{y}] + 2\,\log \widehat{f}(\mathbf{y}) \qquad (2)$$

Regarding LPS, it is a criterion for evaluating the out-of-sample behaviour of different models. This criterion was first introduced by Good (1952) and is intended to examine model performance by comparing its predictive distribution with out-of-sample observations. For this purpose the sample is split into a training and a prediction set. Our prediction set consists of observations corresponding to the last two observed years of every firm in the sample, and the training set contains all the rest. The formula is the following:

$$LPS = -\frac{1}{k}\sum_{i=1}^{k} \log f(y_{i,t_i}|\text{previous data}), \qquad (3)$$

where y_{i,t_i} represents the observations in the predictive set for the k firms in the sample and t_i represents the penultimate time point with observed data for firm i.

3.4. Translog Cost and Profit Models

We use cost and profit functions for the frontier specification in (1), and we represent them with translog multi-product functions. The estimated model is:

[11] The implementation of our models is carried out using the WinBUGS package (see Griffin and Steel, 2007, for a general procedure).

$$
\begin{aligned}
\ln c_{it} = \;& \beta_0 + \sum_{m=1}^{M} \beta_m \ln y_{m_{it}} + \sum_{r=1}^{R} \delta_r \ln p_{r_{it}} + \tfrac{1}{2} \sum_{m=1}^{M} \sum_{n=1}^{M} \beta_{mn} \ln y_{m_{it}} \ln y_{n_{it}} \\
& + \tfrac{1}{2} \sum_{r=1}^{R} \sum_{s=1}^{R} \delta_{rs} \ln p_{r_{it}} \ln p_{s_{it}} + \sum_{m=1}^{M} \sum_{r=1}^{R} \eta_{mr} \ln y_{m_{it}} \ln p_{r_{it}} + \kappa_1 t \\
& + \tfrac{1}{2} \kappa_2 t^2 + \sum_{m=1}^{M} \phi_m t \ln y_{m_{it}} + \sum_{r=1}^{R} \varphi_r t \ln p_{r_{it}} + v_{it} + u_{it} \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_{it} \sim \exp(\lambda_{it}) \\
& \lambda_{it} = exp(\gamma_0 + \sum_{h=1}^{H} \gamma_h z_{h_{it}} + \sum_{j=1}^{J} \gamma^*_{j_i} z^*_{j_{it-1}}),
\end{aligned} \tag{4}
$$

where c_{it} is the total cost or the total profit, y are outputs, p are input prices, and t is a time trend in order to account for technological change. We also account for two types of heterogeneity variables affecting cost and profit inefficiency: A group of bank characteristics modeled in z, which are assumed to have common effects on all banks, and a group of variables z^*, capturing banks' risk-exposure in the previous period and allowed to have specific effects on the inefficiency of each bank. In order to overcome the problem of calculations of logarithms of negative profits, we follow the rescaling method (Berger and Mester, 1997) which corrects profit values by a factor Θ equal to the absolute value of the lowest profit plus one. Linear homogeneity of the cost function is achieved by normalizing total costs and input prices by a chosen input price. Symmetry of the cross-effects is accomplished by imposing $\beta_{mn} = \beta_{nm}, \delta_{rs} = \delta_{sr}$. In the case of the profit function the sign of the inefficiency component u is reversed.

From (4) cost efficiency of individual banks in each period is computed as:

$$CE_{it} = \exp(-u_{it}). \tag{5}$$

In the case of profit efficiency, since a constant has been added in order to allow for profit losses, the efficiency computation is the following (see Berger and Mester, 1997):

$$PE_{it} = \frac{\exp(\ln \pi(p_{it}, y_{it}, t; \boldsymbol{\beta}) - u_{it}) - \Theta}{\exp(\ln \pi(p_{it}, y_{it}, t; \boldsymbol{\beta})) - \Theta}. \tag{6}$$

Returns to scale (RTS) can be derived from the cost function as the sum of output elasticities as follows:

$$RTS = \left(\sum_{m=1}^{M} \frac{\partial \ln C(\mathbf{p}, \mathbf{y}, t)}{\partial \ln y_m} \right)^{-1}, \tag{7}$$

where a RTS measure less than 1 indicates that the production technology present decreasing returns to scale. On the other hand, increasing returns to scale are observed if the RTS measure is larger than 1, while if it is equal to 1 it indicates constant returns to scale.

Finally, technical change (TC) assuming constant returns to scale is given by:

$$TC = -\left(\sum_{m=1}^{M} \frac{\partial \ln C(\mathbf{p}, \mathbf{y}, t)}{\partial t}\right). \tag{8}$$

4. Data

We employ annual data from 31 commercial banks for the period 2002-2012. This is an unbalanced panel data set from the local central bank (*Banco de la República*) and the financial supervisory agency (*Superintendencia Financiera de Colombia*). We follow the financial intermediation approach in which banks employ deposits, labor, and physical capital to produce loans, securities investments, and other financial services.[12] We consider as input prices: the price of deposits (p_1), which is the ratio of interest expenses divided by total deposits; the price of labor (p_2), which is personnel expenses divided by the total number of employees; and the price of physical capital (p_3), which is calculated as the ratio of operating expenses (i.e. non-interest reduced by personnel) to total fixed assets. Thus, these are prices per unit of input. As outputs we consider: loans (y_1) including consumer, commercial, mortgage, and microcredit; securities (y_2), which includes public and private bonds holdings, and other securities investments; and off-balance-sheet (OBS) activities (y_3) measured as the ratio of non-interest income over total income. Non-interest income includes securitization, brokerage services, and management of financial assets for clients, which represent an important source of income for Colombian banks.[13] Total costs are considered as the sum of interest and non-interest costs and total profit as the earned net profit.

We consider two bank-specific characteristics with common effects on the inefficiency of all banks. Those are, size (z_1), measured as the level of total assets; and foreign ownership (z_2), which is a binary variable taking the value of 1 if more than 50% of bank shares are foreign owned; and 0 otherwise. As aforementioned, these effects have been found to be relevant inefficiency drivers in previous studies.

As risk-exposure measures with heterogeneous effects on bank-specific inefficiency, we include measures for credit risk, liquidity, capital, and market risk in accordance with Colombian financial regulation and Basel III standards. Credit risk (z_1^*) is measured as risky loans over total loans.[14] This measure of ex-ante

[12] Hughes and Mester (1993) provide evidence that confirm that deposits should be treated as inputs (see Sealey and Lindley, 1977, for a discussion on the intermediation approach).

[13] In a recent study, Tabak and Tecles (2010) find that omitting OBS as an output over-(under-)estimate cost (profit) efficiency results.

[14] Risky loans are based on internal loan ratings performed by banks according to the Colombian regulation. This measure of ex-ante credit risk has been used before in the literature to identify bank risk-taking in the credit market (see Ioannidou and Penas, 2010).

credit risk may avoid biased efficiency estimations that have been identified when using ex-post credit risk measures such as NPL (see Malikov et al., 2014). Liquidity (z_2^*) is measured as the ratio of liquid assets over total assets, where liquid assets include cash holdings, negotiable and available to sell public and private debt instruments and pledged collateral in repurchase agreement operations. Capitalization (z_3^*) is measured as the ratio of capital equity over total assets. Finally, market risk exposure (z_4^*) is measured as securities investments over total assets. All risk variables are included lagged one-period in order to account for intertemporal effects on inefficiency and avoid reverse causality.

Table 1 exhibits the summary statistics of the main variables described above, where all monetary values are expressed in thousands of U.S. dollars at constant prices from the year 2012.

Table 1: Summary statistics

Variable	**Mean**	**SD**	**Min**	**Max**
Total loans	3,342,012	4,206,436	11,553	28,267,020
Securities	1,265,349	1,339,794	563	6,461,458
OBS	0.0354	0.0299	0.0266	0.0587
Price of deposits	0.0248	0.0121	0.0009	0.0923
Price of labour	36.44	22.30	3.13	142.03
Price of capital	1.92	2.66	0.29	17.30
Total assets	5,503,680	6,425,746	39,699	41,786,469
Credit risk exposure	0.0988	0.0667	0.0019	0.3839
Liquidity ratio	0.2296	0.0945	0.0377	0.8226
Capital ratio	0.1211	0.0757	0.0448	0.7854
Market risk exposure	0.2381	0.1368	0.0013	0.7478
Total cost	1,132,776	1,402,621	15,673	7,722,227
Total profit	76,927	377,974	- 784,642	2,809,771

Source: Colombian central bank and financial supervisory agency.

5. Results

For comparison purposes, we estimate three different cost (C1 to C3) and profit (P1 to P3) models from our proposed specification in (4) by including some restrictions. Models C1 and P1 do not include risk-exposure variables in the inefficiency, so $\gamma_{1i}^*, \gamma_{2i}^*, \gamma_{3i}^*, \gamma_{4i}^* = 0$. Models C2 and P2 include the risk covariates in the inefficiency but restrict them to have a common effect on the inefficiency for all banks; thus, $\gamma_{1i}^*, \gamma_{2i}^*, \gamma_{3i}^*, \gamma_{4i}^* = \gamma_1^*, \gamma_2^*, \gamma_3^*, \gamma_4^*$. Finally, our proposed specification to model random inefficiency coefficients is estimated in models C3 and P3.

Given that our interest is to analyze the effects of size, ownership and risk-exposure on efficiency, we present the estimation results only for the parameters in the inefficiency distribution. Tables 2 and 3, present the posterior mean and probability intervals for the parameters in the cost and profit inefficiency component, respectively. Results for the frontier parameters are presented in the Appendix in Tables A.1 and A.2.[15]

Table 2: Posterior mean and 95% probability intervals of parameters in the inefficiency distribution of cost models

	Model C1		**Model C2**		**Model C3**	
	No risk covariates		Common risk coefficients		Random risk coefficients	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	1.0350	[0.0142, 0.0591]	0.9046	[0.4875, 1.4407]	0.8925	[0.4532, 1.3128]
γ_1 *size*	-0.1981	[-0.2913, -0.0820]	-0.1823	[-0.3041, -0.0762]	-0.1595	[-0.3070, -0.0109]
γ_2 *foreign*	-0.8144	[-1.9580, -0.0943]	-0.6358	[-1.1525, -0.1482]	-0.2198	[-0.4206, -0.0693]
γ_1^* *credit*			0.3058	[0.0845, 0.5280]	0.2863	[0.0932, 0.5816]
γ_2^* *liquidity*			0.2962	[-0.0598, 0.6511]	0.3511	[-0.0718, 0.7160]
γ_3^* *capital*			-1.0823	[-1.5908, -0.5961]	-1.9502	[-2.8485, -1.0214]
γ_4^* *market*			0.0341	[-1.0370, 1.0452]	-0.0054	[-1.0517, 1.0326]
Mean efficiency	0.8934		0.8923		0.7102	
s.d. efficiency	0.0653		0.1466		0.2251	
DIC_3	2982.76		2416.44		2005.79	
LPS	-9.62		-61.57		-91.79	

Note: Values for γ_1^* to γ_4^* in Model C3 correspond to the average posterior distribution of individual coefficients.

5.1. Model Comparison

Model comparison indicators lead to similar conclusions in both the cost and profit models.[16] That is, models including measures of risk exposure improve from models omitting these variables (C1 and P1). This suggests that risk-taking is an important determinant of bank inefficiency. From the models considering risk exposures, those including random coefficients for the risk covariates in the inefficiency distribution (C3 and P3) exhibit the best fit and predictive performance. These results suggest not only that measures of risk exposure are important inefficiency drivers but also that risk has different effects on cost and profit inefficiency of

[15]From the frontier parameter estimates, it is observed that loans, investments, and OBS positively affect cost and input prices in all models. In the case of profits, the relationship is also positive for loans and investments but negative, although not significant, for OBS. This result for OBS was also found by Tabak and Tecles (2010) in an application to the Indian banking sector. However, they found loans and investments to be not significant when OBS is included in both cost and profit models. Regarding input prices, the coefficients are not relevant in the profit models.

[16]Lower values for DIC_3 and LPS indicate better fit and predictive performance.

Table 3: Posterior mean and 95% probability intervals of the inefficiency parameter distributions in profit models

	Model P1		**Model P2**		**Model P3**	
	No risk covariates		Common risk coefficients		Random risk coefficients	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	-0.9668	[-2.4390, 0.3062]	-1.2045	[-2.7145, 0.3825]	-1.4024	[-2.9651, 0.2635]
γ_1 *size*	0.0556	[0.0226, 0.1491]	0.0779	[0.0321, 0.1316]	0.1277	[0.0054, 0.1927]
γ_2 *foreign*	1.0120	[0.6873, 1.3594]	1.0347	[0.6906, 1.3790]	1.0200	[0.4760, 1.5287]
γ_1^* *credit*			-2.0264	[-2.8005, -1.3274]	-1.5812	[-2.5727, -0.6431]
γ_2^* *liquidity*			0.1925	[-0.6021, 1.0655]	0.5437	[-0.3528, 1.3919]
γ_3^* *capital*			-1.4811	[-2.0741, -0.6972]	-1.4367	[-2.1599, -0.5821]
γ_4^* *market*			-0.8884	[-1.5174, -0.2640]	-0.9531	[-1.6614, -0.2650]
Mean efficiency	0.5150		0.6205		0.6714	
s.d. efficiency	0.1638		0.2281		0.3281	
DIC_3	3168.01		2458.10		2360.85	
LPS	-180.01		-302.42		-405.94	

Note: Values for γ_1^* to γ_4^* in Model P3 correspond to the average posterior distribution of individual coefficients.

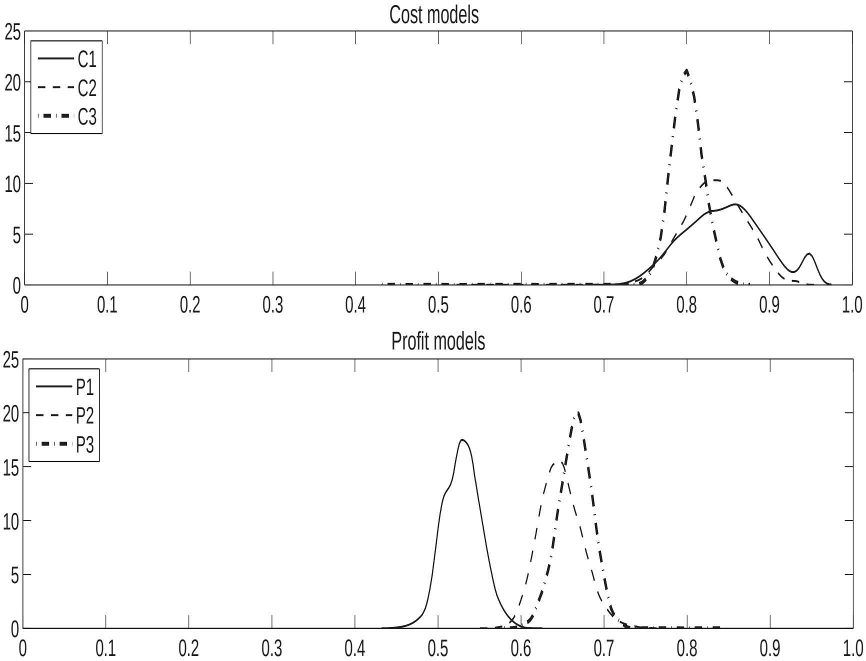
banks with different characteristics. This has important implications for efficiency estimations. In tables 2 and 3, we observe that posterior mean cost and profit efficiency are over- underestimated, respectively, and that their dispersion is lower when risk-exposure measures are not modeled as bank-specific in the inefficiency distribution.

Figure 2 exhibits also differences in the predictive efficiency distributions of cost and profit models. We observe that both location and dispersion of the distributions are affected (see Koetter, 2008, for similar results)). In particular, predictive distributions from models including risk in the inefficiency are more symmetric and those derived from models with random coefficients present less dispersion. Overall, these results evidence the importance of accounting for risk-taking and its associated heterogeneity among banks when estimating bank inefficiency (see Hughes et al., 2001; Koetter, 2008; Pessarossi and Weill, 2015; Radić et al., 2012; Malikov et al., 2014, for previous evidence).

5.2. Inefficiency Determinants

We observe that size and foreign ownership are important inefficiency drivers in all the models. Their effects are negative on cost inefficiency and positive on profit inefficiency. Previous studies have found similar effects. Chen and Liao (2011) found that foreign banks perform better than local banks because they may better deal with risk exposures given cheaper access to funding sources and more diversification. Fries and Taci (2005) found similar results for banks with a majority of foreign ownership in emerging economies. Regarding size, previous studies have found that large institutions tend to exhibit greater efficiency associated with higher scale economies (Bos and Kool, 2006; Wheelock and Wilson,

Figure 2: Predictive distributions of efficiency under cost and profit models



This figure depicts differences in the predictive efficiency distributions of cost and profit models. Models with no risk-taking covariates (C1 and P1), models with common risk coefficients (C2 and P2) and models with random risk coefficients (C3 and P3).

2012; Hughes and Mester, 2013). In previous applications to Colombian banks, both foreign and large banks have also been found to be more cost efficient than local and small banks (Moreno and Estrada, 2013; Sarmiento et al., 2013; Galán et al., 2015).

This relative advantage of large over small banks has been recently reported in the literature as evidence of the *too-big-to-fail* dilemma where larger banks take advantage of their size to obtain funds at lower cost and take on more risk (Santos, 2014). Bertay et al. (2013) analyzed a large sample of banks for 90 countries during the period from 1992-2011 and found that bank interest costs tend to decline with systemic size.

Size and foreign ownership are also key characteristics determining the way credit and market risk, and liquidity and capitalization levels affect cost and profit efficiency. This is identified through the random coefficient models. We analyze these effects by type of banks (i.e. small vs. large and domestic vs. foreign). Figures 3 and 4 present 95% probability intervals of average posterior random coefficients by type of bank in the cost and profit models, respectively. We observe two main results when bank-specific coefficients are estimated. First, some groups of banks are more affected than others taking the same risk exposures. Second, the effects of risk exposures become relevant as inefficiency drivers for some types of banks.

5.2.1. Credit Risk

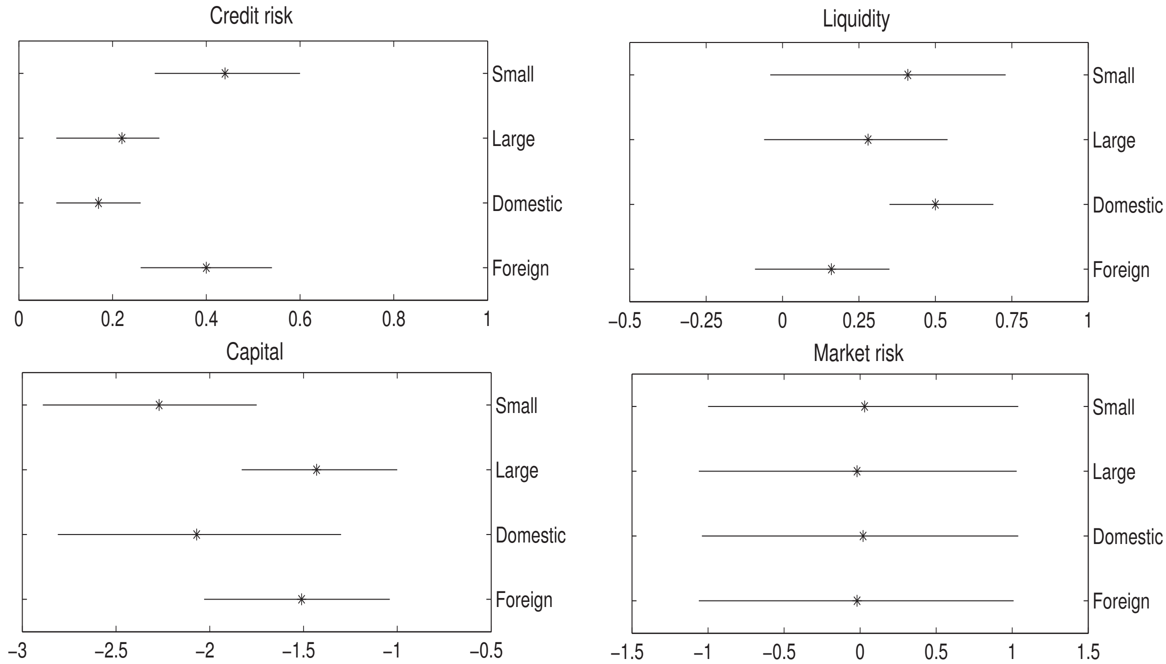
Credit risk is identified as a key determinant of both cost and profit inefficiency though with opposite effects. While credit risk is found to have positive effects on cost inefficiency (i.e. negative effects on cost efficiency), it affects negatively profit inefficiency (i.e. positive effects on profit efficiency). These results are identified in both the fixed and the random coefficients models and may suggest that assuming higher credit risk exposures implies expending more resources on monitoring and administering problem loans. Berger and DeYoung (1997) also found evidence on this negative effect of problem loans on cost efficiency in U.S. banks and argue that extra costs may be represented by additional monitoring, negotiating possible workout arrangements, disposing collateral for possible defaults, defending bank's safety to the market and supervisor, and additional precautions to reserve quality of other loans. On the other hand, in term of profits banks earn extra profits from riskier loans and may have incentives to engage in higher credit risk.

By type of banks, we identify important differences in the way credit risk affect efficiency. Large and domestic banks are found to be less affected in cost efficiency by assuming the same level of credit risk. That is, it is less costly for large and domestic banks to manage problem loans. A possible explanation could be related to the fact that local banks have better information about borrowers which implies that these banks may incur in lower monitoring costs. As to large banks, they may benefit from scale economies that allows them to incur proportionally in lower costs at the same credit risk levels. Regarding profit efficiency, large and foreign banks benefit more from assuming similar levels of credit risk. These types of banks may take advantage of their recognition in order to charge higher interest rates for loans of similar quality or are exploiting market power benefits (see Boyd and De Nicoló, 2005; Wagner, 2010).

5.2.2. Liquidity

Although results from our models with common coefficients suggest that liquidity does not have relevant effects on efficiency of Colombian banks, the random coefficients model identifies an important positive effect of liquidity on cost inefficiency (i.e. negative effect on cost efficiency) of domestic banks. This suggests that holding the same proportion of liquid assets is more costly for local banks. This could be explained by the fact that foreign banks may have greater access to interbank markets and to cheaper sources of funding (Chen and Liao, 2011). In the case of profit efficiency, no differences are found in the way liquidity affects efficiency of banks with different characteristics of size and ownership.

Figure 3: Probability intervals of risk-exposure coefficients by type of bank in cost efficiency model C3



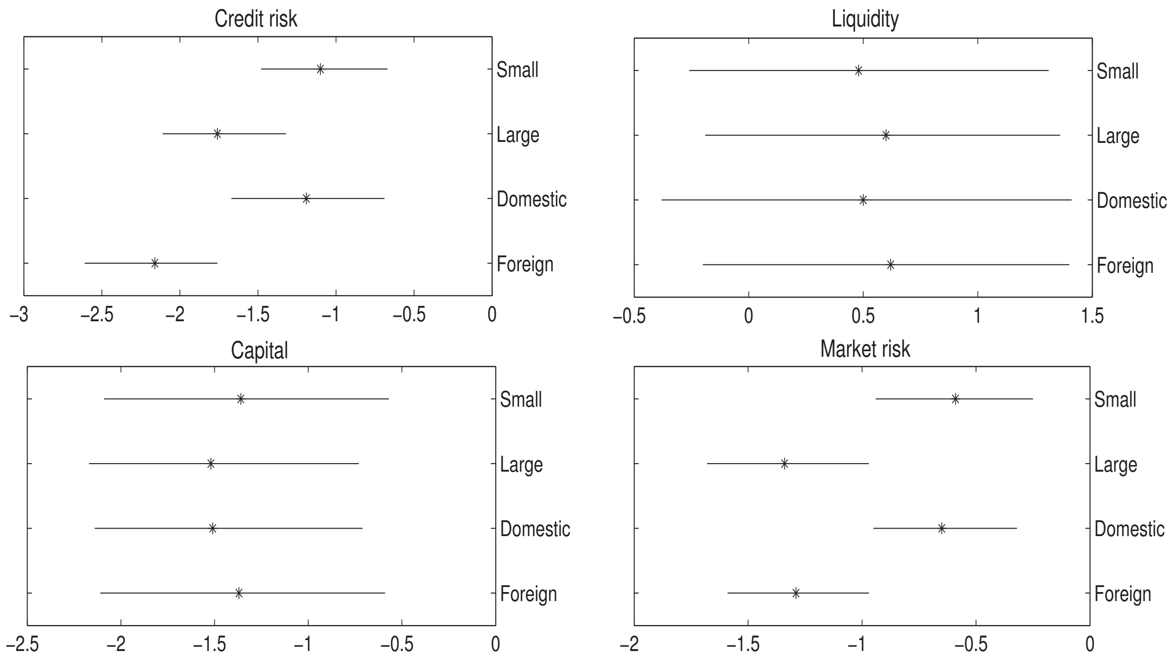
Note: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients.

5.2.3. Capital

We identify that higher capitalization levels lead to higher cost and profit efficiency. Reasons behind these results may be derived from the agency problems between shareholder and managers. Shareholders of highly capitalized banks have more incentives to control better costs and capital allocation than shareholders of thinly capitalized banks. This behavior incentivizes managers to put in practice cost reducing strategies that lead to higher efficiency. Previous studies have also found evidence showing that highly capitalized banks tend to be more efficient than thinly capitalized banks (see Kwan and Eisenbeis, 1997; Fiordelisi et al., 2011; Radić et al., 2012). Berger and DeYoung (1997) also suggest an indirect effect through credit risk. That is, highly capitalized banks have less moral hazard incentives to take on higher risk, and therefore they will incur in less costs.

Regarding differences in the effect of capital on efficiency between banks with different sizes and ownerships, our results may suggest that small and domestic banks benefit more in terms of cost efficiency. However, it is worth to notice that the probability that these estimates are lower than those of large and foreign banks are less than 95%. On this regard, Berger and Bowman (2013) have found that small banks benefit more than large banks from increases in capital specially during the financial crisis. Also, Pessarossi and Weill (2015) have found that domestic banks in China benefit from having higher capital while the effect for foreign banks is not significant. They argue that domestic banks in China have more government guarantees in case of financial distress. This would increase agency costs between shareholders and debtholders, which would become more important than agency costs between shareholders and managers. In terms of profit efficiency, no relevant differences are found between banks with different characteristics.

Figure 4: Probability intervals of risk-exposure coefficients by groups of banks in profit efficiency model P3



Note: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients.

5.2.4. Market Risk

As to market risk, we find no evidence of important effects on cost inefficiency of Colombian banks. This result holds when heterogeneous effects are accounted for in the random coefficients models, suggesting that market risk is not a cost efficiency determinant for any type of bank. Nevertheless, market risk have important negative effects on banks profit inefficiency (i.e. positive effects on profit efficiency). Moreover, the random coefficients model shows strong evidence supporting that these effects are more important for large and foreign banks, which would have greater incentives to engage in more market risk. Large and foreign banks may benefit from having more diversified portfolios and access to cheaper funding sources that allow them to get higher returns on their investments (as reported by Chen and Liao (2011)). Also, large banks are the primary dealers of the Colombian public debt market. This condition allows them to obtain higher profits by selling debt bills to small banks, who use them as collateral to obtain liquidity from the central bank and from the secured money market.

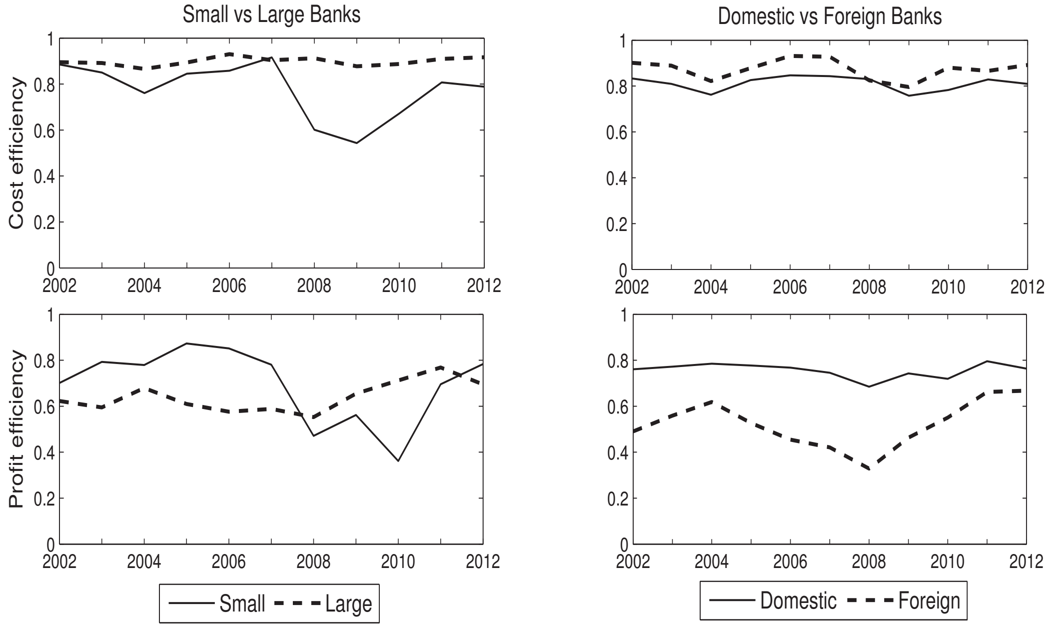
5.3. Efficiency, Technical Change and Returns to Scale

The evolution of cost and profit efficiency over time is presented in Figure 5 by groups of banks. We observe that large and foreign banks exhibit higher cost efficiency levels than small and local banks. A possible explanation for the differences between banks with different sizes may be related to the fact that large banks might be considered by creditors as *too-big-to-fail*, which allows them to have access to cheaper funding sources. Small banks have been more volatile in both cost and profit efficiency over time, specially after the global financial crisis, while large banks have been more stable and present higher cost efficiency over the whole period. This may suggest that large banks are less sensitive to environmental conditions, possibly due to more stable funding sources. In the case of small banks the result might be the opposite because creditors and depositors may ask for higher returns from those banks as a way to exert market discipline (see evidence in Wheelock and Wilson, 2012; Bertay et al., 2013; Hughes and Mester, 2013).

Regarding ownership, although foreign banks present higher cost efficiency than local banks, in terms of profit efficiency they exhibit lower scores and much more volatility over the whole period. The highest difference is observed in 2008 coinciding with the global financial crisis. This suggests that foreign institutions were more affected due to their operations and investments in international markets. Nevertheless, in the last few years, foreign banks have improved and exhibited an increasing trend in profit efficiency.

Finally, we compute technical change and returns to scale from Model C3 and report the results in Table 4 by groups of banks with similar characteristics of size and ownership. In general, we observe technical progress for all types of banks but specially for large and domestic institutions. This can be a consequence of the reorganization processes that these types of institutions have carried out during the period including several M&A. Regarding returns to scale, decreasing returns are observed in the Colombian banking sector, which may suggest low margins for more M&A processes. However, some important differences are found when the analysis is performed by groups of banks. We find that while large and domestic institutions operate at decreasing returns to scale, small and foreign banks exhibit increasing returns to scale. These results coincide with those reported by Galán et al. (2015), who suggest that M&A processes carried out mainly by domestic and large institutions may lead them to be oversized, while small and foreign banks may still present some potential scale gains. Furthermore, the fact that large banks exhibit decreasing returns to scale may confirm that their efficiency gains obey to external sources such as lower funding costs (i.e. deposits, subordinated debt or interbank loans) as a result of implicit government guarantees. On this

Figure 5: Evolution of mean posterior cost and profit efficiency by groups of banks in random coefficient models



regard, Davies and Tracey (2014) evaluated a panel of the largest international commercial banks over the period from 2001 to 2010 and found that large banks benefit from implicit subsidies and that suppressing them makes scale economies disappear. Their results imply that estimated scale economies for large banks are affected by *too-big-to-fail* considerations.

Table 4: TC and RTS by type of bank

Bank type	**TC**	**RTS**
Small	0.0332	1.0473
Large	0.0522	0.9216
Domestic	0.0474	0.9211
Foreign	0.0425	1.0413
All banks	0.0456	0.9618

6. Concluding remarks

Risk-taking is an inherent condition of the banking business. However, traditional studies on bank efficiency had assumed that risk is incorporated into bank output without explicitly modeling its role in explaining inefficiency. Recent studies show that failure to account for risk-taking may lead to biased estimations of bank efficiency and misleading estimates of scale economies and cost elasticities. Likewise, the literature has focused mainly on credit risk and capitalization, omitting other important risks faced by banks.

We present a stochastic frontier model with random inefficiency coefficients, which is able to capture unobserved heterogeneity related to credit, liquidity, capital, and market risk exposures. The model is found to accurately distinguish bank heterogeneity from inefficiency and provides the first empirical evidence on the role of bank risk-taking in the inefficiency of the Colombian banking industry. In line with previous evidence, our findings remark the importance of accounting for size, affiliation and risk exposure in the estimation of bank efficiency (Bos et al., 2009; Radić et al., 2012; Goddard et al., 2014; Pessarossi and Weill, 2015). Cost and profit efficiency are found to be over- underestimated when risk measures are not accurately modeled into the profit and cost function(Hughes et al., 2001; Koetter, 2008; Malikov et al., 2014). We also find that size and foreign ownership are not only important determinants of efficiency but also key characteristics determining the way credit and market risk, and liquidity and capitalization levels affect cost and profit efficiency. The main channels supporting these differences among banks with different characteristics are related to monitoring costs, diversification, information asymmetries, agency costs, risk-taking incentives, among others.

We find that higher credit risk exposures lead to lower cost efficiency that can be associated with greater expenditures on monitoring and administering problem loans. However, our findings suggest that these costs are lower for large and domestic banks. Large banks may benefit from scale economies that allows them to incur proportionally in lower costs at the same credit risk levels, while local banks may incur in lower monitoring costs given that they have better information about borrowers. We also find credit risk to be associated with higher profit efficiency and that large and foreign banks benefit more from assuming similar levels of credit risk.

We provide evidence to support the hypothesis that capital requirements and buffers may contribute to enhance banking efficiency (Chortareas et al., 2012; Barth et al., 2013; Pessarossi and Weill, 2015). We identify that higher capitalization levels lead to higher efficiency in both costs and profits, specially for small and domestic banks. This can be related to agency problems between shareholders and managers. Shareholders of highly capitalized banks have more incentives to control better costs and capital allocation, while managers of these institutions have less moral hazard incentives to take on higher credit risk. However, we find that those marginal benefits from capitalization are lower for small banks after 2008 coinciding with the global financial crisis and the regulatory changes on capital ratios and credit risk implemented by the Colombian regulator. This finding may imply that the positive effect of capitalization on the incentives of both shareholders and managers to be more efficient can be limited when the cost of raising capital increases.

Our results also identify positive effects of market risk on profit efficiency. In particular, large and foreign institutions are found to have greater incentives to engage in more market risk (Radić et al., 2012). These types of banks may benefit of having more diversified portfolios and access to cheaper funding sources that allow them to obtain higher returns on their investments. Large banks also benefit from being the primary dealers of the Colombian public debt market which enhances their efficiency gains from the trading activity in this market.

Finally, large banks are found to present higher efficiency than small institutions and to be less affected by the financial crisis (Berger and Bowman, 2013). Moreover, the fact that large banks face lower costs and present incentives to take on more risk in credit and securities constitutes a signal for regulators to closely monitor the behavior of these type of banks and their riskiness. Decreasing returns to scale exhibited by large banks may also suggest that their cost and profit efficiency gains obey to external sources such as lower funding costs (i.e. deposits, subordinated debt or interbank loans) as a result of implicit government guarantees (Davies and Tracey, 2014). Thus, regulators should also consider alternative measures to limit risk-taking incentives associated with the fact that large banks may benefit of being considered as *too-big-to-fail*.

Overall, bank efficiency estimations should account for the influence of risk-taking along with other bank-characteristics of size and ownership. We study these interactions by employing random coefficients models which provide a suitable approach to deal with this type of heterogeneity in banking production models. Banks cost and profit efficiency measures that account for risk-taking may constitute a useful indicator for financial stability considerations given that banks with lower efficiency have been found to be more prone to future bank fails and tend to engage on more risk (Berger and DeYoung, 1997; Podpiera and Weill, 2008). Regulators should be aware not only of the consequences of macroprudential regulation on bank performance, but also of the different effects that polices intended to discourage risk exposure have on banks with different characteristics.

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Agoraki, M., M. Delis, and F. Pasiouras (2011). Regulations, competition and bank risk-taking in transition countries. *Journal of Financial Stability 7*, 38–48.

Aigner, D., C. Lovell, and P. Schmidt (1977). Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics 6*, 21–37.

Altunbas, Y., S. Carbo, E. Gardener, and P. Molyneux (2007). Examining the relationships between capital, risk and efficiency in European banking. *European Financial Management 13 (10)*, 49–70.

Anginer, D., A. Demirguc-Kunt, H. Huizinga, and M. Kebin (2013). How does corporate governance affect bank capitalization strategies? Policy Research Working Paper 6636, The World Bank.

Barajas, A., R. Steiner, and A. Salazar (2002). The impact of liberalization and foreign direct investment in Colombia's financial sector. *Journal of Development Economics 23*, 157–196.

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

Berger, A. and C. Bowman (2013). How does capital affect bank performance during financial crises? *Journal of Financial Economics 109*, 146–176.

Berger, A. and R. DeYoung (1997). Problem loans and cost efficiency in commercial banks. *Journal of Banking and Finance 21(6)*, 849–870.

Berger, A. and L. Mester (1997). Journal of banking and finance. *Inside the Black Box: What Explains Differences in the Efficiencies of Financial Institutions? 21*, 895–947.

Bertay, A., A. Demirgüç-Kunt, and H. Huizinga (2013). Do we need big banks? Evidence on performance, strategy and market discipline. *Journal of Financial Intermediation 22*, 532–558.

BIS (2010). Basel III: International framework for liquidity risk measurement, standards and monitoring. Basel Committee on Banking Supervision December, Bank for International Settlements.

BIS (2011). Basel III: A global regulatory framework for more resilient banks and banking systems. Basel Committee on Banking Supervision June, Bank for International Settlements.

Bos, J., M. Koetter, J. Kolari, and C. Kool (2009). Effects of heterogeneity on bank efficiency scores. *European Journal of Operational Research 195*, 251–261.

Bos, J. and C. Kool (2006). Bank efficiency: The role of bank strategy and local market conditions. *Journal of Banking and Finance 30*, 1953–1974.

Boyd, J. and G. De Nicoló (2005). The theory of bank risk taking and competition revisited. *Journal of Finance 60*, 1329–1343.

Brunnermeier, M. and L. Pedersen (2009). Market liquidity and funding liquidity. *Review of Financial Studies 22*(6), 2201–2238.

Carvalho, F., L. Paula, and J. Williams (2014). Banking in latin america. In A. Berger, P. Molyneux, and J. Wilson (Eds.), *The Oxford Handbook of Banking, Second Edition*. Oxford University Press, Inc.

Celeux, G., F. Forbes, C. Robert, and D. Titterington (2006). Deviance information criteria for missing data models. *Bayesian Analysis 4*, 651–674.

Chen, S. and C. Liao (2011). Are foreign banks more profitable than domestic banks? Home- and host-country effects of banking market structure, governance, and supervision. *Journal of Banking and Finance 35*, 819–839.

Chortareas, G., C. Girardone, and A. Ventouri (2012). Bank supervision, regulation, and efficiency: Evidence from the European Union. *Journal of Financial Stability 8*, 292–302.

Clavijo, S., C. Rojas, C. Salamanca, G. Montoya, and C. Rizo (2006). Mergers and acquisitions in the Colombian financial sector: Impact on efficiency (1990-2005). *Icfai Journal of Mergers and Acquisitions 3*, 38–61.

Davies, R. and B. Tracey (2014). Too big to be efficient? the impact of implicit subsidies on estimates of scale economies for banks. *Journal of Money Credit and Banking 46*, 219–253.

Estrada, D. and P. Osorio (2004). Efectos del capital financiero en la eficiencia del sistema bancario colombiano. *Ensayos Sobre Política Económica 47*, 162–201.

Feng, G. and X. Zhang (2012). Productivity and efficiency at large and community banks in the US: A Bayesian true random effects stochastic distance frontier analysis. *Journal of Banking and Finance 36*, 1883–1895.

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

Fries, S. and A. Taci (2005). Cost efficiency of banks in transition: Evidence from 289 banks in 15 post-communist countries. *Journal of Banking and Finance 29*, 55–81.

Galán, J., H. Veiga, and M. Wiper (2014). Bayesian estimation of inefficiency heterogeneity in stochastic frontier models. *Journal of Productivity Analysis 42*, 85–101.

Galán, J., H. Veiga, and M. Wiper (2015). Dynamic effects in inefficiency: Evidence from the Colombian banking sector. *European Journal of Operational Research 240*, 562–571.

Goddard, J., P. Molyneux, and J. Williams (2014). Dealing with cross-firm heterogeneity in bank efficiency estimates: Some evidence from Latin America. *Journal of Banking and Finance 40*, 130–142.

Gomez-Gonzalez, J. a. N. K. (2009). Bank failure: Evidence from the colombian financial crisis. *The International Journal of Business and Finance Research 3*, 15–31.

Good, I. (1952). Rational decisions. *Journal of the Royal Statistical Society B 14*, 107–114.

Greene, W. (2005). Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Econometrics 126*, 269–303.

Griffin, J. and M. Steel (2004). Semiparametric Bayesian inference for stochastic frontier models. *Journal of Econometrics 123*, 121–152.

Griffin, J. and M. Steel (2007). Bayesian stochastic frontier analysis using WinBUGS. *Journal of Productivity Analysis 27*, 163–176.

Hughes, J. and L. Mester (1993). A quality and risk-adjusted cost function for banks: Evidence on the 'too-big-to-fail" doctrine. *Journal of Productivity Analysis 4 (3)*, 293–315.

Hughes, J. and L. Mester (2013). Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function. *Journal of Financial Intermediation 22 (4)*, 559–585.

Hughes, J., L. Mester, and C. Moon (2001). Are scale economies in banking elusive or illusive?: Evidence obtained by incorporating capital structure and risk-taking into models of bank production. *Journal of Banking and Finance 25 (12)*, 2169–2208.

Ioannidou, M. and M. Penas (2010). Deposit insurance and bank risk-taking: Evidence from internal loan ratings. *Journal of Financial Intermediation 19*, 95–115.

Koetter, M. (2008). The stability of efficiency rankings when risk-preferences and objectives are different. *The European Journal of Finance 14 (2)*, 115–135.

Koop, G., M. Steel, and J. Osiewalski (1995). Posterior analysis of stochastic frontier models using Gibbs sampling. *Computational Statistics 10*, 353–373.

Kwan, S. and R. Eisenbeis (1997). Bank risk, capitalization and operating efficiency. *Journal of Financial Services Research 12 (2)*, 117–131.

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

León, C., C. Machado, F. Cepeda, and M. Sarmiento (2012). Systemic risk in large value payment systems in colombia: a network topology and payments simulation approach. In M. Hellqvist and T. Laine (Eds.), *Diagnostics for the financial markets - computational studies of payment system, Simulator Seminar Proceedings, 2009-2011*. Bank of Finland.

Lepetit, L., E. Nys, P. Rous, and A. Tarazi (2008). Bank income structure and risk: an empirical analysis of European banks. *Journal of Banking and Finance 32 (8)*, 1452–1467.

Malikov, E., D. Restrepo-Tobón, and S. Kumbhakar (2014). Estimation of banking technology under credit uncertainty. *Empirical Economics DOI:10.1007/s00181-014-0849-z*, in press.

Meeusen, W. and J. van den Broeck (1977). Efficiency estimation from Cobb-Douglas production functions with composed errors. *International Economic Review 8*, 435–444.

Moreno, D. and D. Estrada (2013). Colombian bank efficiency and the role of market structure. Temas de Estabilidad Financiera, No. 76, Banco de la República.

Pessarossi, P. and L. Weill (2015). Do capital requirements affect cost efficiency? evidence from china. *Journal of Financial Stability 19*, 119–127.

Podpiera, J. and L. Weill (2008). Bad luck or bad management? Emerging banking market experience. *Journal of Financial Stability 4 (2)*, 135–148.

Radić, N., F. Fiordelisi, and C. Girardone (2012). Efficiency and risk-taking in pre-crisis investment banks. *Journal of Financial Services Research 41(1)*, 81–101.

Rajan, R. (2006). Has finance made the world riskier? *European Financial Management 12 (4)*, 499–533.

Santos, J. (2014). Evidence from the bond market on banks' "too big to fail" subsidy. *Economic Policy Review 20(2)*, 29–39.

Sarmiento, M., A. Cepeda, H. Mutis, and J. Perez (2013). Nueva evidencia sobre la eficiencia de la banca colombiana: Una medición con modelos de frontera no-paramétricos. Archivos de Economía 392, Departamento Nacional de Planeación.

Sealey, C. and J. Lindley (1977). Inputs, outputs and a theory of production and cost at depository financial institutions. *Journal of Finance 32*, 1252–1266.

Shleifer, A. and R. Vishny (2010). Unstable banking. *Journal of Financial Economics 97*(3), 306–318.

Spiegelhalter, D., N. Best, B. Carlin, and A. van der Linde (2002). Bayesian measures of model complexity and fit. *Journal of the Royal Statistical Society 64*(4), 583–616.

Tabak, B., G. Craveiro, and D. Cajueiro (2011). Bank efficiency and default in Brazil: Causality tests. Working Paper Series, No. 235, Central Bank of Brazil.

Tabak, B. and P. Tecles (2010). Estimating a Bayesian stochastic frontier for the Indian banking system. *International Journal of Production Economics 125*, 96–110.

Uribe, J. and H. Vargas (2002). Financial reform, crisis and consolidation in Colombia. Borradores de Economía, No. 204, Banco de la República.

van den Broeck, J., G. Koop, J. Osiewalski, and M. Steel (1994). Stochastic frontier models: A Bayesian perspective. *Journal of Econometrics 61*, 273–303.

Wagner, W. (2010). Loan market competition and bank risk-taking. *Journal of Financial Services Research 37*, 71–81.

Wang, H. and P. Schmidt (2002). One step and two step estimation of the effects of exogenous variables on technical efficiency levels. *Journal of Productivity Analysis 18*, 129–144.

Wheelock, D. C. and P. W. Wilson (2012). Do large banks have lower costs? New estimates of returns to scale for U.S. banks. *Journal of Money, Credit and Banking 44(1)*, 171–199.

Williams, J. (2004). Determining management behavior in European banking. *Journal of Banking and Finance 28(10)*, 2427–2460.

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

Appendix

Table A.1: Posterior mean and 95% probability intervals of frontier parameter distributions in cost models

	Model C1		Model C2		Model C3	
	No risk covariates		Common risk coefficients		Random risk coefficients	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
β_0	9.789	[-3.249,24.840]	3.698	[-9.591,20.04]	7.205	[-1.754,18.03]
β_1	3.025	[0.6511,5.195]	4.031	[1.639,6.182]	2.914	[1.242,4.282]
β_2	3.391	[1.609,5.336]	4.586	[2.841,6.214]	3.538	[2.436,4.606]
β_3	-0.199	[-0.391,0.013]	-0.261	[-0.436,0.064]	-0.212	[-0.339,0.077]
β_{11}	-0.457	[-0.713,-0.201]	-0.511	[-0.775,-0.251]	-0.399	[-0.584,-0.171]
β_{12}	0.267	[0.0725,0.459]	0.307	[0.092,0.515]	0.231	[0.052,0.388]
β_{13}	0.017	[0.0024,0.033]	0.015	[0.004,0.027]	0.013	[0.003,0.023]
β_{22}	0.010	[-0.108,0.146]	0.029	[-0.107,0.183]	0.048	[-0.071,0.195]
β_{23}	-0.003	[-0.019,0.013]	-0.001	[-0.013,0.010]	0.001	[-0.005,0.008]
β_{33}	0.001	[-0.003,0.004]	0.001	[-0.002,0.004]	-0.001	[-0.004,0.000]
δ_1	-1.678	[-4.807,2.347]	-4.381	[-7.473,-0.846]	-3.307	[-5.343,-1.122]
δ_2	0.820	[-1.730,3.045]	2.272	[-0.244,4.200]	1.645	[-0.389,2.898]
δ_{11}	0.179	[-0.141,0.571]	-0.029	[-0.301,0.264]	-0.043	[-0.253,0.171]
δ_{12}	-0.001	[-0.372,0.318]	0.095	[-0.182,0.331]	0.083	[-0.075,0.235]
δ_{22}	-0.077	[-0.443,0.343]	-0.150	[-0.419,0.177]	-0.204	[-0.381,-0.031]
η_{11}	0.170	[-0.110,0.416]	0.319	[0.015,0.547]	0.235	[0.072,0.394]
η_{12}	0.123	[-0.071,0.319]	0.036	[-0.144,0.223]	0.111	[-0.009,0.226]
η_{21}	0.005	[-0.115,0.140]	-0.044	[-0.154,0.075]	-0.030	[-0.107,0.044]
η_{22}	-0.124	[-0.272,0.008]	-0.090	[-0.207,0.028]	-0.114	[-0.188,-0.034]
η_{31}	-0.009	[-0.029,0.017]	-0.016	[-0.033,0.005]	-0.009	[-0.020,0.003]
η_{32}	-0.006	[-0.023,0.013]	0.004	[-0.014,0.020]	-0.003	[-0.014,0.008]
κ_1	-0.336	[-1.018,0.411]	-0.543	[-1.096,0.015]	-0.511	[-0.849,-0.169]
κ_2	0.007	[-0.013,0.028]	-0.005	[-0.019,0.010]	-0.001	[-0.011,0.009]
ϕ_1	0.066	[0.010,0.119]	0.083	[0.033,0.127]	0.078	[0.043,0.109]
ϕ_2	-0.023	[-0.055,0.014]	-0.022	[-0.049,0.009]	-0.030	[-0.051,-0.009]
ϕ_3	-0.003	[-0.007,0.000]	-0.002	[-0.006,0.000]	-0.002	[-0.003,-0.001]
φ_1	0.049	[-0.021,0.128]	0.044	[-0.010,0.101]	0.024	[-0.008,0.057]
φ_2	-0.054	[-0.136,0.030]	-0.052	[-0.107,0.005]	-0.044	[-0.073,-0.013]

Table A.2: Posterior mean and 95% probability intervals of the frontier parameter distributions in profit models

	Model P1		Model P2		Model P3	
	No risk covariates		Common risk coefficients		Random risk coefficients	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
β_0	5.6560	[4.4570, 6.9950]	5.8790	[4.9180, 6.8760]	5.3440	[4.1010, 6.7390]
β_1	0.0533	[0.0023, 0.1381]	0.0296	[0.0036, 0.0621]	0.0873	[0.0039, 0.1750]
β_2	0.0927	[0.0015, 0.2178]	0.0792	[0.0070, 0.2172]	0.0401	[0.0015, 0.1079]
β_3	0.0475	[0.0018, 0.1184]	0.0516	[0.0047, 0.1095]	0.0571	[0.0024, 0.1810]
β_{11}	0.0712	[0.0192, 0.1282]	0.0780	[0.0292, 0.1290]	0.0873	[-0.0033, 0.1604]
β_{12}	0.0186	[-0.0382, 0.0698]	0.0119	[-0.0388, 0.0597]	0.0022	[-0.0694, 0.0835]
β_{13}	-0.0048	[-0.0110, 0.0008]	-0.0044	[-0.0095, 0.0007]	-0.0029	[-0.0099, 0.0034]
β_{22}	0.0116	[-0.0350, 0.0591]	0.0157	[-0.0265, 0.0576]	0.0033	[-0.0754, 0.0694]
β_{23}	0.0018	[-0.0021, 0.0057]	0.0015	[-0.0018, 0.0048]	0.0012	[-0.0029, 0.0054]
β_{33}	0.0011	[-0.0009, 0.0031]	0.0010	[-0.0007, 0.0027]	0.0014	[-0.0003, 0.0032]
δ_1	0.1544	[0.0046, 0.4351]	0.1484	[0.0108, 0.3585]	0.0959	[0.0034, 0.2848]
δ_2	0.1802	[0.0065, 0.6177]	0.1726	[0.0126, 0.4098]	0.1515	[0.0050, 0.4716]
δ_{11}	0.2195	[0.0861, 0.3221]	0.1866	[0.0581, 0.2884]	0.0397	[-0.1571, 0.2172]
δ_{12}	-0.2212	[-0.3014, -0.1322]	-0.2062	[-0.2777, -0.1289]	-0.1467	[-0.2555, -0.034]
δ_{22}	0.2010	[0.0978, 0.3008]	0.1857	[0.0980, 0.2720]	0.1831	[0.0751, 0.2814]
η_{11}	0.1508	[0.0996, 0.2006]	0.1492	[0.1040, 0.1930]	0.1623	[0.0868, 0.2325]
η_{12}	-0.0298	[-0.0766, 0.0154]	-0.0289	[-0.0680, 0.0113]	-0.0354	[-0.0929, 0.0279]
η_{21}	-0.0175	[-0.0744, 0.0267]	-0.0283	[-0.0858, 0.0165]	-0.0979	[-0.1702, -0.0233]
η_{22}	-0.0836	[-0.1286, -0.0365]	-0.0752	[-0.1165, -0.0324]	-0.0439	[-0.1008, 0.0130]
η_{31}	0.0012	[-0.0059, 0.0094]	0.0017	[-0.0042, 0.0080]	0.0033	[-0.0035, 0.0117]
η_{32}	0.0035	[-0.0040, 0.0103]	0.0023	[-0.0043, 0.0083]	-0.0016	[-0.0104, 0.0057]
κ_1	-0.3458	[-0.5945, -0.0978]	-0.3589	[-0.5671, -0.1485]	-0.3092	[-0.5264, -0.0984]
κ_2	0.0022	[-0.0070, 0.0111]	0.0022	[-0.0054, 0.0096]	0.0051	[-0.0025, 0.0125]
ϕ_1	0.0364	[0.0141, 0.0591]	0.0373	[0.0184, 0.0562]	0.0364	[0.0184, 0.0562]
ϕ_2	-0.0344	[-0.0513, -0.0179]	-0.0349	[-0.0489, -0.0209]	-0.0359	[-0.0489, -0.0209]
ϕ_3	0.0002	[-0.0013, 0.0018]	0.0001	[-0.0012, 0.0013]	-0.0006	[-0.0012, 0.0013]
φ_1	-0.0401	[-0.0680, -0.0127]	-0.0417	[-0.0653, -0.0184]	-0.0388	[-0.0651, -0.0131]
φ_2	0.0167	[-0.0067, 0.0408]	0.0166	[-0.0029, 0.0364]	0.0099	[-0.0105, 0.0314]

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