Emerging Markets Review 32 (2017) 52–73

Contents lists available at ScienceDirect

Emerging Markets Review

journal homepage: www.elsevier.com/locate/emr

The influence of risk-taking on bank efficiency: Evidence from Colombia☆

Miguel Sarmiento[a,b,*], Jorge E. Galán[c]

[a] Financial Stability Department, Banco de la República, Carrera 7 # 14-78, Bogotá, Colombia
[b] CentER and European Banking Center, Tilburg University, The Netherlands
[c] Financial Stability Department, Banco de España, Alcalá 48, Madrid 28014, Spain

ARTICLE INFO

Article history:
Received 2 May 2016
Received in revised form 4 October 2016
Accepted 6 May 2017
Available online 14 May 2017

JEL classification:
C11
C23
C51
D24
G21
G32

Keywords:
Bank efficiency
Bayesian inference
Heterogeneity
Random parameters
Risk-taking
Stochastic frontier models

ABSTRACT

This paper shows evidence on the influence of risk-taking on bank efficiency in emerging markets and identifies heterogeneity in the way risk affects banks with different characteristics. We fit a stochastic frontier model with random inefficiency parameters to a sample of Colombian banks. The model provides accurate cost and profit efficiency estimates. The effects of risk-taking on efficiency vary with size and affiliation. Large and foreign banks benefit more from higher exposure to credit and market risk, while domestic and small banks from being more capitalised. We identify some channels explaining these differences and provide insights for prudential regulation.

1. Introduction

The modern banking theory shows that banks' performance is subject to uncertainty derived from the behavior of borrowers, depositors and financial markets in which they interact. This type of uncertainty is commonly referred as bank risk-taking that reflects the amount of risk that banks are willing to tolerate, which in turn 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 on more risk-taking. However, risk has a cost that is mainly related with banking regulation and market discipline (i.e. capital ratios or loan loss provisions) (Hughes and Mester, 2010; Flannery, 2010). During the global financial crisis of 2007–2008 excessive risk-taking was associated with banking runs,

☆ The opinions and statements in this article do not necessarily coincide with those of Banco de la República, Banco de España or the Eurosystem.

* Corresponding author at: Banco de la República, Carrera 7 # 14-78, Bogotá, Colombia; CentER, Tilburg University, 5000 Tilburg, The Netherlands.
E-mail addresses: nsarmipa@banrep.gov.co (M. Sarmiento), jorge.galan@bde.es (J.E. Galán).

http://dx.doi.org/10.1016/j.ememar.2017.05.007
1566-0141/© 2017 Published by Elsevier B.V.

fire-sales, reduced lending and financial fragility (Brunnermeier and Pedersen, 2009; Shleifer and Vishny, 2010; Beltratti and Stulz, 2012). 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, 2013). Overall, these regulatory 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 has become an important concern in the literature.

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 strand of literature has focused on the relationship between credit risk, capitalisation and bank efficiency (see the seminal work of Berger and DeYoung, 1997). Most of studies exploring these relationships have found that highly capitalised banks are more cost efficient than banks with low capitalisation levels (Kwan and Eisenbeis, 1997; Altunbas et al., 2007; 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 (Williams, 2004; Podpiera and Weill, 2008; Tabak et al., 2011).

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 evidence shows 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., 2015).

However, most of studies modeling the effects of risk-taking on efficiency incorporate only proxies for credit risk (usually ex-post measures such as non-performing loans, NPL), and omit other important risks faced by banks such as those related to insolvency, market and liquidity, which may have relevant effects on bank efficiency. On this regard, Radić et al. (2012) account for several risk measures as inefficiency determinants of investment banks in G-7 countries and find that insolvency and liquidity risk have relevant effects on cost and profit efficiency.

Evidence on the effects of risk-taking on bank efficiency in emerging economies is more limited. Bitar et al. (2016) find that compliance with the Basel capital requirements enhances bank protection against risk, and improves efficiency and profitability in the Middle East and North African countries. For the same countries, Naceur and Omran (2011) find bank capitalisation and credit risk to be positively associated with cost efficiency. Hou et al. (2014) evaluate the efficiency of the Chinese banking system accounting for measures of risk and market structure and find that risk-taking have positive effects on technical efficiency, which in turn has led to an accumulation of risk in the banking sector. Pessarossi and Weill (2015) find a significant and positive influence of a higher capital ratio on cost efficiency of Chinese banks during 2004–2009. However, they find interesting differences when the effect of capitalisation is allowed to vary with the type of ownership. In particular, foreign banks are found to decrease their efficiency when their capital ratio increases. On this regard, 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).

In this context, effects of risk-taking on bank efficiency may be heterogeneous among banks with different types of ownership and sizes. In particular, foreign institutions in emerging countries may present different practices of corporate governance which jointly with specific characteristics of diversification and the expertise of their foreign parents make them to react in a different way than domestic banks to changes in risk exposures (Chen and Liao, 2011; Lensink et al., 2008). Also, small and large banks may present different elasticities of risk exposure given the differences in the incentives they experience when size increases (Bertay et al., 2013; Tabak et al., 2013). Thus, accounting for heterogeneity related to risk exposure is relevant when measuring bank efficiency.

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 able to limit risk-taking. These measures were initially motivated by a profound financial crisis at the end of 1990s that affected several emerging economies (e.g. Russia, South Korea, Thailand and Brazil) and 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 (Daude and Pascal, 2015; Galán et al., 2015; Sarmiento et al., 2013). Therefore, recognizing differences in the way risk affects different types of banks becomes relevant in order to get more accurate efficiency estimations and a complete understanding of the effects of risk and prudential 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 distinguish these effects between banks with different sizes and affiliations. In particular, we account for the influence of credit, liquidity, capital, and market risk exposures and identify differences in the effects that similar levels of risk have on efficiency. Thus, 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 Goddard et al. (2014) and Williams (2012) in which random parameters are used in order to account for unobserved technological and inefficiency heterogeneity. However, we estimate in a single step heterogeneous effects of risk on bank inefficiency. Thus, we fill this gap in the literature. 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

(see Tabak and Tecles, 2010; Hou et al., 2015, for some recent applications of the Bayesian approach to banks efficiency measurement). The model is estimated for the Colombian banking sector using quarterly 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. Hence, we provide evidence on the influence of risk in bank efficiency from emerging markets.

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 changes in risk exposures affect cost and profit efficiency. Domestic and small banks benefit more from being highly capitalised, while large and foreign banks benefit from higher exposure to credit and market risk. We find that large 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, which are related to monitoring costs, diversification, information asymmetries, agency costs, and risk-taking incentives. Overall, we show that risk-taking plays a crucial role in explaining banking efficiency and the importance of allowing for heterogeneous effects among banks when modeling it.

The rest of this paper contains six additional sections. In Section 2, we describe the Colombian banking sector performance and regulation. Section 3 presents the proposed specification, the Bayesian inference, comparison criteria and the empirical models. Section 4 describes the data. In Section 5, we present and analyze the main results. In Section 6, we perform two different robustness exercises. Section 7 concludes the paper and discusses some regulatory implications.

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).

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 turmoil and led to a profound financial crisis. The external shock from the Asian financial crisis led to capital outflows and exchange rate deterioration. At local level, the economic downturn and the raise of real interest rates forced to a rapid deterioration of loan quality and eroded the solvency of the financial sector. Previous studies reveal that the financial sector deterioration was related with low loan loss provisions and tiny capitalisation levels (Gomez-Gonzalez and Kiefer, 2009) . Between 1998 and 2001, several banking institutions failed and other were merged. Banking institutions specialized in mortgage loans were absorbed by large commercial banks. In consequence, the number of banking institutions fell from 100 in 1998 to 57 in 2001 from which only 31 continued as commercial banks. Also, 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 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 (as proposed in Basel II). 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 capital quality (Tier 1 and Tier 2). Finally, a short-term liquidity ratio (LR) was required for banks to hedge from liquidity mismatches.[4]

[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.

[2] Provisions vary according to borrowers rating, type of credit (i.e. consumer, corporate, mortgage, etc.) and whether the loan has collateral or not.

[3] Capital ratio (CR) should be greater than 9% and is defined as equity capital (CE) over risk 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 meet 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 2006–2007 played an important role in limiting excessive credit growth, currency mismatches and thus to avoid contagion from the global financial crisis of 2007–2008 (see López et al., 2014; Gómez et al., 2016).[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 an 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 their participation in the money market for short-term liquidity boosted. Several M&A processes were also carried out, concentrating financial services in a few but large institutions. As a result, increased risk exposures has been observed.[6] This has required the regulator to closely monitor credit and market risk and to face the challenges of dealing with systemic financial institutions (see León et al., 2012; Sarmiento et al., 2017).

Fig. 1 shows the evolution of ratios related to credit, liquidity, capital and market risk over the period 2002–2012 for 31 commercial banks that operated during this period. The sample is classified 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 capitalisation 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 2007–2008 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 trend may be related with the introduction of the use of risky loans as an indicator for loan loss provisions in 2002 and the dynamic provision scheme since 2006; even during a period of credit expansion and high economic growth (López et al., 2014). 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 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 90s, 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 until the global financial crisis of 2007–2008 heightened, afterwards efficiency and productivity decreased considerably. 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. 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. Daude and Pascal (2015) documented that in spite of Colombian banks have relatively higher efficiency levels than other Latin American banks, both efficiency and the degree of market contestability are lower compared with banks from other emerging markets. The authors argue that both conditions are associated with the relatively higher intermediation costs of the Colombian banking sector. However, previous applications have not studied the influence of risk-taking on efficiency of Colombian banks, which has a crucial role in explaining bank behavior.

[5] In 2006, a new scheme of countercyclical provisions that enhanced the provision requirements on commercial and consumer loans was implemented by the financial supervisor *Superintendecia Financiera de Colombia* (FSC). Besides, the central bank established a marginal reserve requirement in order to attenuate both loan growth and leverage of the private sector. Lastly, to prevent potential arbitrages and to limit a potential substitution from local funding to external borrowing, the central bank reactivated a reserve requirement for short-term external borrowing and a limit on exchange rate derivatives exposure (see Gómez et al., 2016, for details of these measures and their impact on bank lending from 2005 to 2009 in Colombia.)

[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.

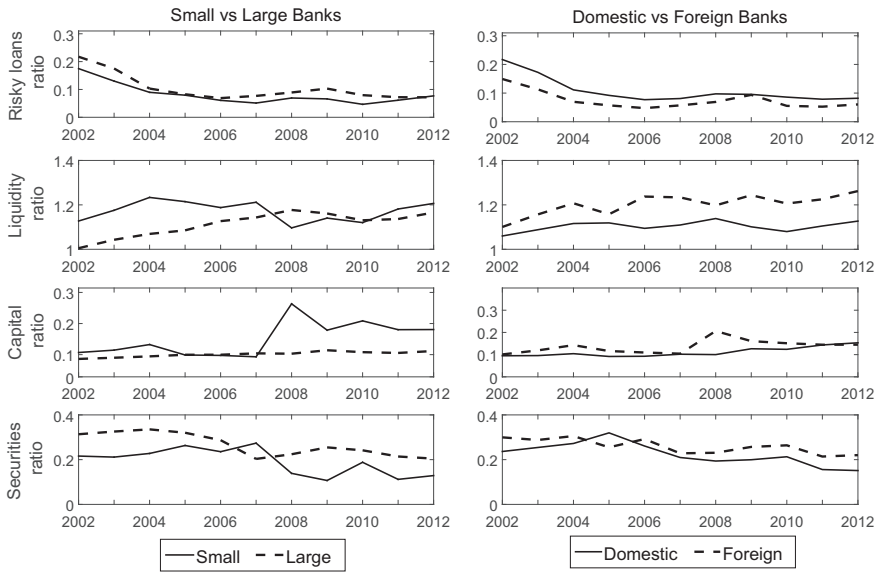

Fig. 1. Evolution of risk exposure measures by type of bank 2002–2012.

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. 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 document that risk exposure measures affect directly the inefficiency distribution.

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 efficiency, 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 models with random parameters in the inefficiency distribution perform better in distinguishing heterogeneity from inefficiency as well as important differences on cost efficiency estimations. Williams (2012) applies a model with random parameters both in the frontier and in the inefficiency distribution in order to test the quiet life hypothesis in Latin American banks. However, the author follows a two-step procedure where cost efficiency is regressed on a market power index and other bank characteristics, which may lead to biased and inconsistent efficiency estimations (see Wang and Schmidt, 2002).

In this context, our proposal is intended to model unobserved inefficiency 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) and

[8] In contrast, the main non-parametric 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.

[9] Greene (2005) proposes different methods to deal with this kind of heterogeneity both in the frontier and in the inefficiency distribution. 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.

Williams (2012) in the use of random parameters in the inefficiency component. However, we propose to estimate the coefficients associated to the observed covariates in the inefficiency distribution as random. This allows us to obtain in a single stage bank-specific estimates of the effects of risk exposure measures on cost and profit efficiency. This specification is more flexible than imposing interactions of observed covariates with different characteristics 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:

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

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 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}, $\boldsymbol{\gamma}_i$ is a vector of firm-specific parameters intended to capture differences in the effects of covariates across banks on inefficiency, and $\mathbf{z}_{it}$ contains a set of heterogeneity variables with bank-specific effects.

In particular, the random coefficients are intended to capture differences in the way similar changes on risk exposures affect efficiency of different types of banks. This specification is also flexible in the sense that some covariates can be modeled with fixed coefficients just by adding constraints of the type $\gamma_i = \gamma$ to the corresponding parameters.

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: $\boldsymbol{\beta} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_\beta)$ where $\boldsymbol{\Sigma}_\beta^{-1}$ 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 $\sigma_v^{-2} \sim G\left(a_{\sigma_v^{-2}}, b_{\sigma_v^{-2}}\right)$ with priors set to 0.01 for the shape and rate parameters, respectively.

Regarding the inefficiency component, its distribution is assumed to be exponential: $u_{it}|\boldsymbol{\gamma}_i, \mathbf{z_{it}} \sim Exp(\exp(\mathbf{z_{it}}\boldsymbol{\gamma}_i))$. For the firm-specific inefficiency heterogeneity coefficients, a hierarchical structure is defined, where $\boldsymbol{\gamma}_i \sim N(\boldsymbol{\gamma}, \boldsymbol{\Sigma}_\gamma)$ and $\boldsymbol{\gamma} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_\gamma)$ with priors for the diagonal precision matrix $\boldsymbol{\Sigma}_\gamma^{-1}$ equal to 0.1 for all the coefficients. In the case we want to restrict the inefficiency covariates to be common to all the observations we define $\boldsymbol{\gamma}$ as above. Sensitivity analysis is performed to the use of an exponential prior distribution for $\boldsymbol{\gamma}$.[10] Results show convergence to roughly the same values after the number of iterations described below. Following Tabak and Tecles (2010), we also explore the sensitivity of the empirical results to the use of a gamma distribution for the inefficiency component, where $u_{it}|\boldsymbol{\gamma}_i, \mathbf{z_{it}} \sim Gamma(2, \exp(\mathbf{z_{it}}\boldsymbol{\gamma}_i))$. Results are robust to the use of the alternative inefficiency distribution (see Appendix).

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 $DIC = 2\bar{D}(\theta) - D(\bar{\theta})$. However, using an estimator of the density $f(y|\theta)$ 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:

$$DIC_3 = -4E_\theta\left[\log f\left(\mathbf{y}|\theta\right)|\mathbf{y}\right] + 2\ \log \widehat{f}\left(\mathbf{y}\right). \tag{2}$$

[10] In this case, the inefficiency parameters are chosen to be centered in a given prior mean efficiency value r^* following the procedure in Griffin and Steel (2007), where $\exp(\boldsymbol{\gamma}) \sim Exp(-lnr^*)$.

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

Regarding LPS, it is a criterion for evaluating the out-of-sample behavior 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:

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

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 Eq. (1), and we represent them with translog multi-product functions. The estimated model is:

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

where c represents the total cost, y_m represent the m outputs, p_r are the r input prices, and t is a time trend in order to account for technological change. We also allow accounting for two types of inefficiency covariates affecting cost and profit inefficiency: A group of h bank characteristics modeled in z_h, which are assumed to have common effects on all banks, and a group of j variables in z_j^*, capturing banks' risk exposure in the previous period and allowed to have specific effects on the inefficiency of each bank. Note that risk covariates are lagged one period to avoid endogenous bank risk taking. 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 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 dependent variable is the total profit and the sign of the inefficiency component u is reversed.[12]

From Eq. (4), cost/profit efficiency of individual banks in each period is computed as:

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

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

$$RTS = \left(\sum_{m=1}^{M} \frac{\partial \ln C\left(\mathbf{x}, \mathbf{y}, t\right)}{\partial \ln y_m}\right)^{-1}, \tag{6}$$

where a RTS measure less than 1 indicates that the production technology present decreasing returns to scale (DRS). On the other hand, increasing returns to scale (IRS) 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:

$$TC = -\left(\frac{\partial \ln C(\mathbf{x}, \mathbf{y}, t)}{\partial t}\right), \tag{7}$$

where negative values of TC indicate technical regress while positive values would imply technical progress.

[12] Note that we use the alternative profit function where banks are seen as price-setters in the output market but price-takers in the input market. This allows to account for imperfect competition, unmeasured differences in output quality and not completely variable outputs (Berger and Mester, 1997)

4. Data

We employ quarterly data from 31 commercial banks operating during the period 2002–2012. This is an unbalanced panel data set composed by 848 bank-level observations provided by the Colombian Central Bank (*Banco de la República*) and the FSC. We only include commercial banks in our sample as they employ a relatively similar technology.[13] We follow the financial intermediation approach in which banks employ deposits, labor, and physical capital to produce loans, securities investments, and other financial services.[14] 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), calculated as the ratio of operating expenses (i.e. non-interest reduced by personnel) to total fixed assets. 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 banks.[15] 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, we include measures for credit risk, liquidity, capitalisation, and market risk in accordance with the literature and the Colombian financial regulation. Usually, credit risk has been identified as a source of bank inefficiency (Berger and DeYoung, 1997; Williams, 2004). Our measure of credit risk (z_1^*) is computed as the ratio of risky loans over total loans.[16] The higher the share of risky loans the higher loan loss provisions required by the regulator. This measure of ex-ante 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., 2015).[17] 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. Higher liquid assets prevent banks from maturity mismatches albeit holding those assets can be costless as they have shorter maturities and thus lower returns. Handorf (2014) documents that liquidity has a cost that reduces bank profits via a lower net interest spread. Capitalisation (z_3^*) is measured as the ratio of capital equity over total assets. Our measure of capitalisation is based on two important features. First, Colombian regulation establishes that foreign banks should hold the same minimum capital than local banks in order to operate. This is because foreign banks operate as subsidiaries rather than branches in Colombia, and in turn they have to hold their own capital. Therefore, our measure of capitalisation is comparable across banks with different ownerships. Second, we argue that differences in capitalisation levels may signal banks risk appetite and influence their performance (as in Hughes and Mester, 1998; Pessarossi and Weill, 2015). Market risk exposure (z_4^*) is measured as securities investments over total assets. Banks involved in more investment activities may exhibit efficiency gains from diversification (Radić et al., 2012). Lastly, it is important to remark that all risk variables are included lagged one-period in order to account for inter-temporal 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. Since we are interested in analyzing the differences between small and large banks and foreign and domestic banks, we also present summary statistics disaggregated by these four groups of banks in Table A.1 in the Appendix.[18]

5. Results

Due to our interest in the effects of risk exposure measures as inefficiency determinants, we estimate three different cost (C1 to C3) and profit (P1 to P3) models from our proposed specification in Eq. (4) by including some restrictions on the parameters associated to risk variables and holding size and foreign ownership as covariates in all the models. 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

[13] During our period of analysis, other credit institutions operated in Colombia. However, they are small credit institutions specialized in retail loans and leasing activities which may operate under a different technology than commercial banks (Hughes et al., 2001) . Moreover, those credit institutions only have activity in some markets while commercial banks behave in all credit markets (i.e. mortgage, commercial, consumer, microcredit, as well as in the money and securities markets. Therefore, our analysis focuses only on commercial banks).

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

[15] Lozano-Vivas and Pasiouras (2014) evidence the importance of including OBS when measuring cost and profit bank efficiency adjusted by risk. Tabak and Tecles (2010) also find that omitting OBS as an output over- (under-)estimate cost (profit) efficiency results.

[16] Risky loans are based on internal loan ratings performed by banks according to the Colombian regulation. Measures of ex-ante credit risk are more appropriated to identify bank risk-taking in the credit market (see Ioannidou and Penas, 2010).

[17] We perform a robustness check by using NPL as measure of credit risk instead. Results confirm that our ex-ante measure of risky loans captures better the risk-taking incentives of banks (see Section 6).

[18] To control for the impact of outliers we drop a total of 6 observations from 2 banks (3 in each case) because of those observations presented extreme values in terms of capital and liquidity ratios. We do not observe an impact from dropping those observations in our results.

Table 1
Summary statistics total sample.

Variable	Mean	Median	SD	Min	Max
Total loans	3,207,295	1,988,658	3,911,162	9383	28,267,020
Securities	1,228,382	838,960	1,255,500	204	6,666,803
OBS	0.0439	0.0345	0.0358	0.0001	0.2650
Price of deposits	0.0066	0.0063	0.0028	0.0004	0.0254
Price of labor	9.0645	7.6186	5.7835	0.0499	66.7323
Price of capital	0.4816	0.2781	0.7507	0.0029	8.8976
Total assets	5,296,408	3,635,674	5,973,928	52,309	41,786,468
Credit risk exposure	0.1110	0.0867	0.0752	0.0037	0.4740
Liquidity ratio	0.2210	0.2060	0.1020	0.0214	0.5800
Capital ratio	0.1160	0.1030	0.0581	0.0448	0.4970
Market risk exposure	0.2400	0.2170	0.1340	0.0005	0.7650
Total cost	295,747	173,610	384,895	5946	3,546,014
Total profit	20,044	− 755	99,533	− 261,771	756,685

Source: Colombian Central Bank and FSC. The total number of observations is 848.

inefficiency but restrict them to have a common effect on the inefficiency for all banks; thus, $\gamma^*_{1i}, \gamma^*_{2i}, \gamma^*_{3i}, \gamma^*_{4i} = \gamma^*_1, \gamma^*_2, \gamma^*_3, \gamma^*_4$. Models C3 and P3 include the random inefficiency coefficients for the risk exposure variables.[19]

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 components, respectively. Results for the frontier parameters are presented in the Appendix Tables A.2 and A.3.[20]

Model comparison indicators lead to similar conclusions in both the cost and profit models.[21] 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 efficiency. 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 efficiency drivers but also that risk has different effects on cost and profit efficiency of 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.

We also find differences in the predictive efficiency distributions of cost and profit models (see Fig. A1 in the Appendix). 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 efficiency (see Hughes et al., 2001; Pessarossi and Weill, 2015; Radić et al., 2012; Malikov et al., 2015, for previous evidence).

5.1. Efficiency determinants

We observe that size and foreign ownership are important efficiency drivers in all the models. Their effects are positive on cost efficiency and negative on profit efficiency. Previous studies have found similar effects. Chen and Liao (2011) document 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) find similar results for banks with a majority of foreign ownership in emerging economies. Sturm and Williams (2008) argue that banks from more financially sophisticated nations are more efficient. Curi et al. (2015) document that during the financial crisis subsidiaries perform better than branches. Interestingly, our findings suggest that foreign banks that operate as subsidiaries in Colombia exhibit higher efficiency than local banks.

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, 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

[19] We also estimate one additional specification for comparison purposes (models C4 and P4). These models include the risk exposure covariates in the frontier rather than in the inefficiency distribution. Results are shown in the Appendix and exhibit that any of these covariates are relevant when these variables are included in the frontier. This would support the inclusion of these variables as inefficiency drivers. Recently, Radić et al. (2012) also found evidence to support that risk exposure is more relevant affecting the inefficiency distribution than the frontier.

[20] 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.

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

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		Fixed risk coefficients		Random risk coefficients	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	1.7158*	[0.9464,2.4853]	0.7982*	[0.2801,1.2322]	0.7586*	[0.2662,1.0968]
γ_1 *size*	−0.3915*	[−0.5443,−0.2386]	−0.3013*	[−0.5546,−0.048]	−0.2871*	[−0.5284,−0.0458]
γ_2 *foreign*	−1.5727*	[−2.5448,−0.6006]	−1.2914*	[−2.0442,−0.5386]	−0.8792*	[−1.3917,−0.3667]
γ_1^* *credit*			0.8087*	[0.2632,1.4193]	0.7363*	[0.3783,1.1390]
γ_2^* *liquidity*			0.7494*	[0.2891,1.2097]	0.8243*	[0.1009,1.3935]
γ_3^* *capital*			−1.2505*	[−1.9249,−0.576]	−2.1452*	[−2.9732,−0.9802]
γ_4^* *market*			−0.2269*	[−0.3838,−0.07]	−0.2722*	[−0.5605,−0.084]
Mean efficiency		0.9087		0.9031		0.7102
SD efficiency		0.0982		0.1109		0.1477
DIC_3		2237.07		1812.33		1359.87
LPS		−12.03		−76.96		−114.74

Note: Values for γ_1^* to γ_4^* in Model C3 correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC.
Negative coefficients imply positive effects on cost efficiency and the opposite is true for positive coefficients.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

(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 to 2011 and found that bank interest costs tend to decline with systemic size. Interestingly, we show in the next section that scale economies are not the driving forces of higher efficiency gains from large Colombian banks which may suggest evidence on TBTF implicit subsidies.

Size and foreign ownership are also key characteristics determining the way credit and market risk, and liquidity and capitalisation 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). On this regard, our approach is close to the one in Pessarossi and Weill (2015), who study the effects of capital on the efficiency of Chinese banks with different sizes and affiliations. However, we include additional measures of risk and perform an analysis a posteriori after allowing for bank-specific coefficients instead of estimating interactions. Figs. 2 and 3 present 95% probability intervals of average posterior random coefficients by type of bank in the cost and profit models, respectively.[22] These figures allow us to observe graphically whether the effects of different types of risks on the efficiency of a group of banks are different than those of the respective benchmark group with a probability greater than 95% and, at the same time, if the estimated coefficients for each group are different from 0 with a probability greater than 95%.[23]

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 efficiency drivers for some types of banks. We explain in detail these effects in the following subsections by differentiating for type of risk.

5.1.1. Credit risk

Credit risk is identified as a key determinant of both cost and profit efficiency though with opposite effects. While credit risk is found to have negative effects on cost efficiency, it affects positively profit efficiency. These results are observed 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 are 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. In emerging economies, Kirkpatrick et al. (2008) document that bad loans tend to increase bank production costs, reflecting inefficiency in lending. On the other hand, in terms of profit efficiency results indicate that banks may have incentives to engage in higher credit risk given that they earn higher returns from riskier loans (Malikov et al., 2015).

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,

[22] These are the average of the values for each bank-specific parameter at every iteration of the MCMC.
[23] The former is true if the 95% probability intervals of the respective benchmark groups do not overlap each other, and the latter is true if the corespondent intervals do not contain the 0.

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		Fixed risk coefficients		Random risk coefficients	
	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	−0.9282*	[−1.0649,−0.7916]	−1.1810*	[−1.3774,−0.9847]	−1.2622*	[−1.472,−1.0523]
γ_1 *size*	0.5633*	[0.4765,0.6501]	0.6635*	[0.5619,0.7651]	0.6385*	[0.5407,0.7363]
γ_2 *foreign*	0.4563*	[0.6873,1.3594]	0.4456*	[0.1848,0.7064]	0.5100*	[0.2115,0.8085]
γ_1^* *credit*			−1.7314*	[−3.1426,−0.3201]	−1.42308*	[−2.583,−0.2631]
γ_2^* *liquidity*			0.4893*	[0.0599,0.9187]	0.8930*	[0.1093,1.6766]
γ_3^* *capital*			−1.7583*	[−2.3555,−1.1611]	−1.7240*	[−2.3096,−1.1385]
γ_4^* *market*			−0.8969*	[−1.6564,−0.1373]	−1.0484*	[−1.8384,−0.4484]
Mean efficiency		0.5643		0.5787		0.6883
SD efficiency		0.1448		0.1758		0.2068
DIC_3		2534.41		1843.58		1763.09
LPS		−198.01		−362.90		−424.47

Note: Values for γ_1^* to γ_4^* in Model P3 correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC.
Negative coefficients imply positive effects on profit efficiency and the opposite is true for positive coefficients.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

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).

5.1.2. Liquidity

Results from our models with fixed and random coefficients suggest that liquidity has relevant effects on the efficiency of Colombian banks. The random coefficients model identifies an important negative effect of liquidity on cost efficiency of domestic and small banks. This suggests that holding the same proportion of liquid assets is more costly for local and small banks compared with foreign and large banks, respectively. 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). Similarly, large banks may have higher access to alternative sources of funding. Angelini et al. (2011) and Sarmiento (2016) have found that large banks benefit from lower funding costs in money markets, which may explain the lower impact of holding liquid assets on their cots efficiency.

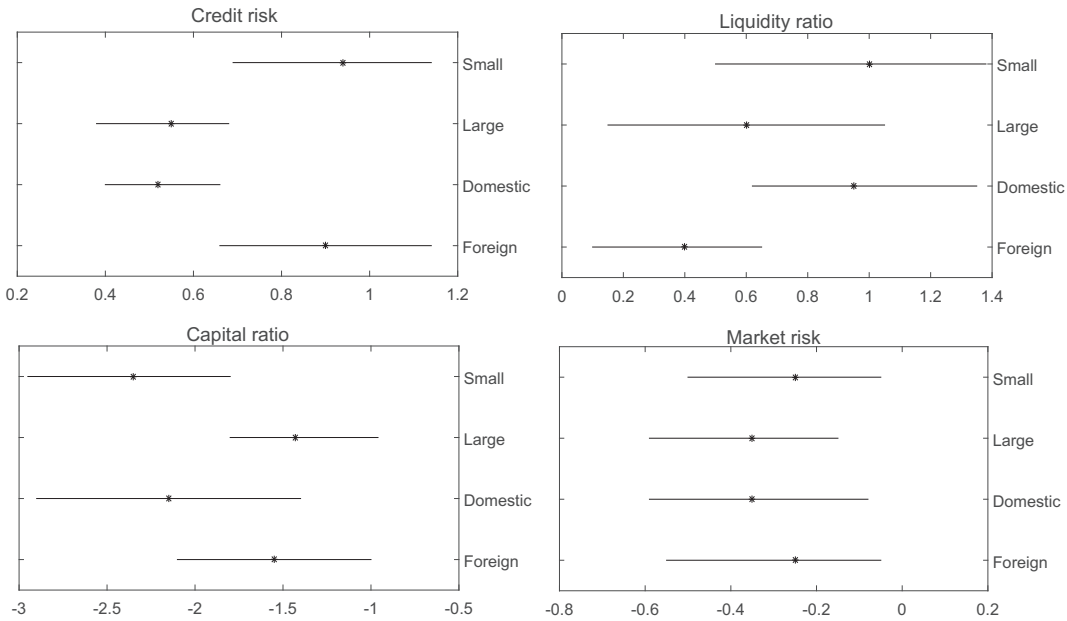

Fig. 2. Probability intervals of risk exposure coefficients by type of bank in cost efficiency model C3. Note: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients for each group of banks. These are the average of the values for each bank-specific parameter at every iteration of the MCMC. If the intervals do not overlap each other, the posterior estimates for one group are different from the other with probability greater than 95%. If the interval do not contain the value of 0, risk affects efficiency of that group of banks with a probability greater than 95%. Negative values imply a positive effect of risk on efficiency and positive values imply a negative effect of risk on efficiency.

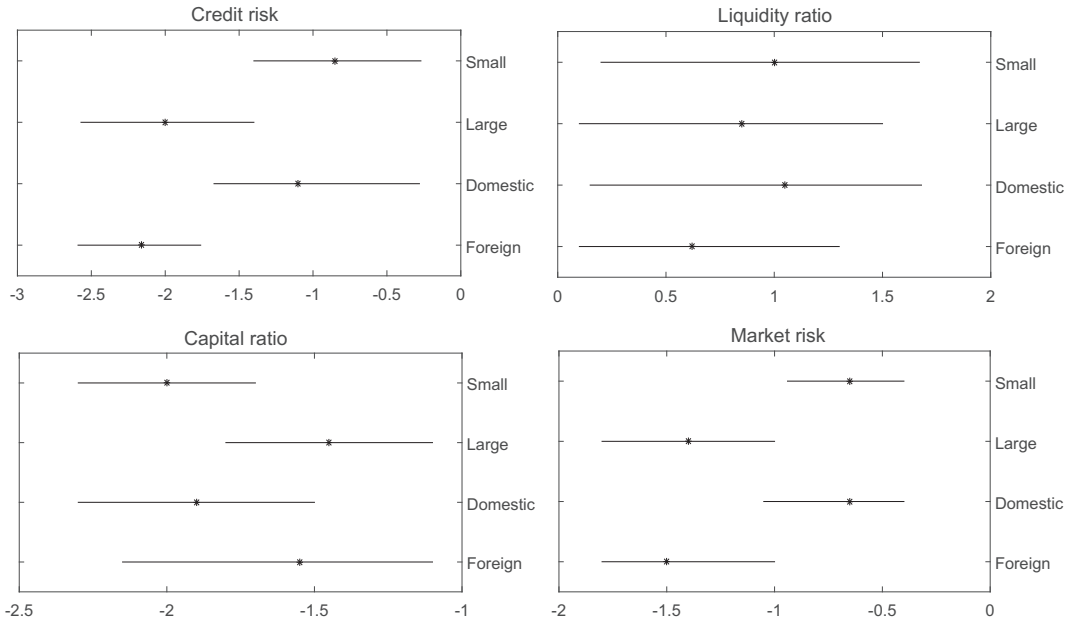

Fig. 3. Probability intervals of risk exposure coefficients by groups of banks in profit efficiency model P3. Note: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients for each group of banks. These are the average of the values for each bank-specific parameter at every iteration of the MCMC. If the intervals do not overlap each other, the posterior estimates for one group are different from the other with probability greater than 95%. If the interval do not contain the value of 0, risk affects efficiency of that group of banks with a probability greater than 95%. Negative values imply a positive effect of risk on efficiency and positive values imply a negative effect of risk on efficiency.

We also find that holding higher liquid assets reduces profit efficiency in both models, possibly due to those assets usually have lower returns. Differences in the way liquidity affects profit efficiency of banks with different characteristics are less relevant. However, the average impact of liquidity on profit efficiency tends to be greater for domestic banks than for foreign banks.

5.1.3. Capitalisation

We identify that higher capitalisation levels lead to higher cost and profit efficiency. Reasons behind these results may be derived from the agency problems between shareholders and managers. Shareholders of highly capitalised banks have more incentives to control better costs and capital allocation than those of thinly capitalised banks. This incentivizes better corporate governance mechanisms that may lead to efficiency improvements. Berger and DeYoung (1997) also suggest an indirect effect through credit risk. That is, highly capitalised banks have less moral hazard incentives to take on higher risk, and therefore they will incur in less costs. Previous studies have found that highly capitalised banks tend to be more efficient than less capitalised banks in developed countries (Kwan and Eisenbeis, 1997; Fiordelisi et al., 2011; Radić et al., 2012) and emerging economies as well (Naceur and Omran, 2011; De Jonghe et al., 2012; Pessarossi and Weill, 2015).

Results indicate that the effect of capitalisation on efficiency differs between banks with different sizes and ownerships. We find that small and domestic banks benefit more from higher capital ratios in both cost and profit efficiency. However, it is worth to notice that the probability that these estimates are lower than those of large and foreign banks is less than 95%. On this regard, Berger and Bowman (2013) document that small banks benefited more than large banks from increases in capital during the global financial crisis of 2008. Pessarossi and Weill (2015) show that domestic banks in China benefit from having higher capital while the effect for foreign banks is not significant. They argue that Chinese domestic banks have more government guarantees in case of financial distress. This would increase agency costs between shareholders and debt-holders, which would become more important than agency costs between shareholders and managers.

5.1.4. Market risk

As to market risk, we find that holding more investments in the bank's portfolio enhances bank efficiency. This result may reflect the benefits from diversification as banks usually invest in private and public bonds to manage liquidity mismatches (Lozano-Vivas and Pasiouras, 2014). Moreover, this result holds when heterogeneous effects are accounted for in the random coefficients models suggesting that market risk is a cost efficiency determinant for any type of bank. Market risk is also found to have positive effects on banks profit efficiency. In this case, the random coefficients model shows strong evidence supporting that these effects are more relevant for large and foreign banks, which would have greater incentives to engage in more market risk. Foreign banks may benefit from their parents expertise on trading securities (Lensink et al., 2008), while large banks may take advantage from being the primary dealers of the Colombian public debt market. The latter condition allows large banks to obtain profits by selling public debt bills to small banks that have to use them as collateral to hedge liquidity either from the

central bank or the secured money market (Sarmiento, 2016). Moreover, 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 (Chen and Liao, 2011). However, it is important to remark that the fact that large and foreign banks tend to rely more on unstable sources of funding (i.e. money market funding) and to exhibit more market-based-income may lead to financial fragility and to enhance systemic risk (Brunnermeier et al., 2012; Laeven et al., 2016).

5.2. Efficiency, technical change and returns to scale

The evolution of cost and profit efficiency over time is presented in Fig. 4 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 (see Curi et al., 2015). Nevertheless, in the last few years, foreign banks have improved and exhibited an increasing trend in profit efficiency.

We compute technical change and returns to scale from Model C3. As we did for the random coefficient parameters, we compute average posterior distributions by groups of banks, which allows us to simultaneously identify through probability intervals whether these groups of banks present technical progress/regress or scale economies/diseconomies and whether there are differences between groups of banks with certain probability.[24] Fig. 5 shows the 95% probability intervals by groups of banks with similar characteristics of size and ownership. In general, we observe that with a probability higher than 95% all types of banks exhibit technical progress and that it is on average higher for large and domestic institutions, which can be a consequence of the reorganization processes that these institutions carried out during the period including several M&A. Regarding returns to scale, some important differences are found between groups of banks. We observe that while large institutions operate at decreasing returns to scale, small and foreign banks exhibit increasing returns to scale.[25] 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 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. See also Beccalli et al. (2015) for similar results in the European banking system.

6. Robustness check

We perform several robustness exercises. First, we split the sample and search for structural changes in the risk-efficiency relationship after 2008. Second, we use an alternative measure of credit risk and check whether using an ex-post measure affects the estimations. Third, we check whether our findings on the relationship between risk and efficiency change when a profitability measure is included as an additional efficiency driver. Finally, as aforementioned we also check robustness of our results to the use of an alternative prior distribution for the inefficiency component.[26]

6.1. Structural changes after 2008

As presented above, the evolution of cost and profit efficiency of Colombian banks exhibits changes in magnitude and volatility after 2008. In fact, changes in their credit and market risk exposures, and capital and liquidity ratios were observed. Thus, we check whether the global financial crisis and the regulatory changes adopted after 2008 represented an structural change in

[24] We evaluate technical change and returns to scale at every iteration of the MCMC for each bank and then we average the values at each iteration. This procedure is consistent with the way we assess the effect of the risk-taking measures in the inefficiency models.

[25] The probability interval of RTS for domestic banks contains the value of 1, which do not allow us to conclude about decreasing returns to scale for these type of banks with a probability higher than 95%.

[26] Being a publicly listed bank may also be a characteristic driving bank efficiency (see Radić et al., 2012, for some evidence in U.S. investment banks.) However, this distinction in the Colombian banking sector is non-meaningful given that only a handful of banks are publicly listed (5 of 31), all of them being large banks.

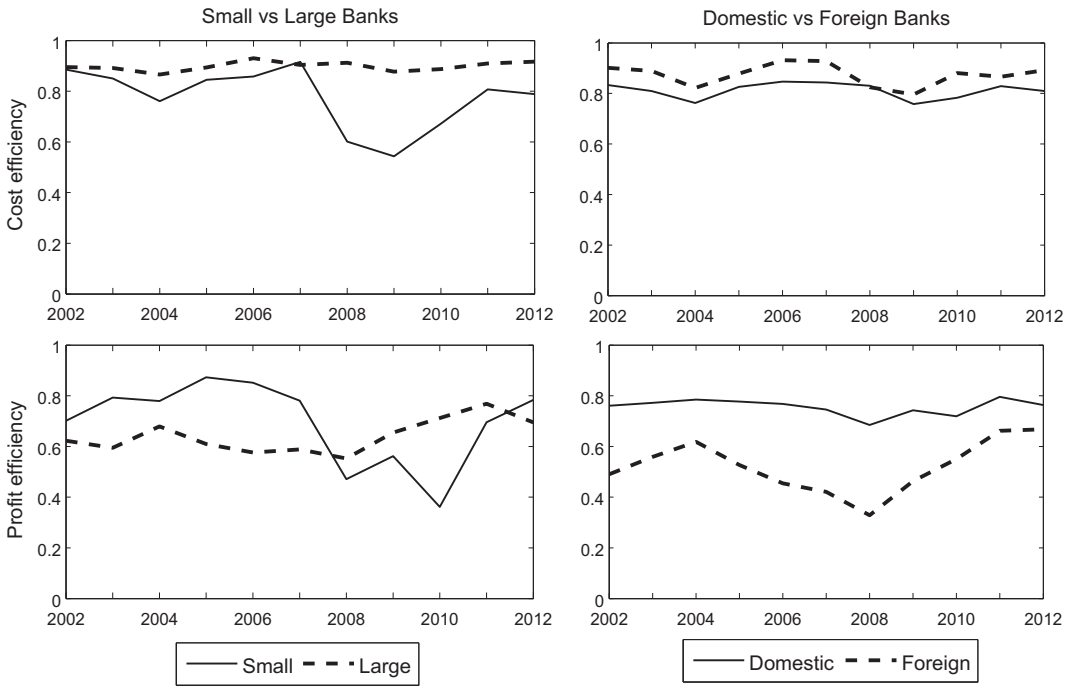

Fig. 4. Evolution of mean posterior cost and profit efficiency by groups of banks in random coefficient models. Note: Figures plot the mean of the average posterior cost and profit efficiency distribution for each group of banks and period. These are the average of the posterior efficiency values for each bank at every iteration of the MCMC.

the risk-efficiency relationship of Colombian banks. We split the sample and estimate two cost and profit inefficiency random coefficients models: one for the period 2002–2007 (Models C5 and P5) and other for the period 2008–2012 (Models C6 and P6). Results of estimations are presented in Table 4. We observe that, in general, there are no relevant changes in the way credit risk, capital, liquidity, and market risk affects efficiency of Colombian banks.

However, when random coefficients are analyzed by groups of banks, some changes in the effects of capital and credit risk over cost and profit efficiency of small banks are identified. Fig. 6 shows the 95% probability intervals of average posterior capital and credit risk coefficients for small and large banks in the four new estimated models. We observe that the negative effect

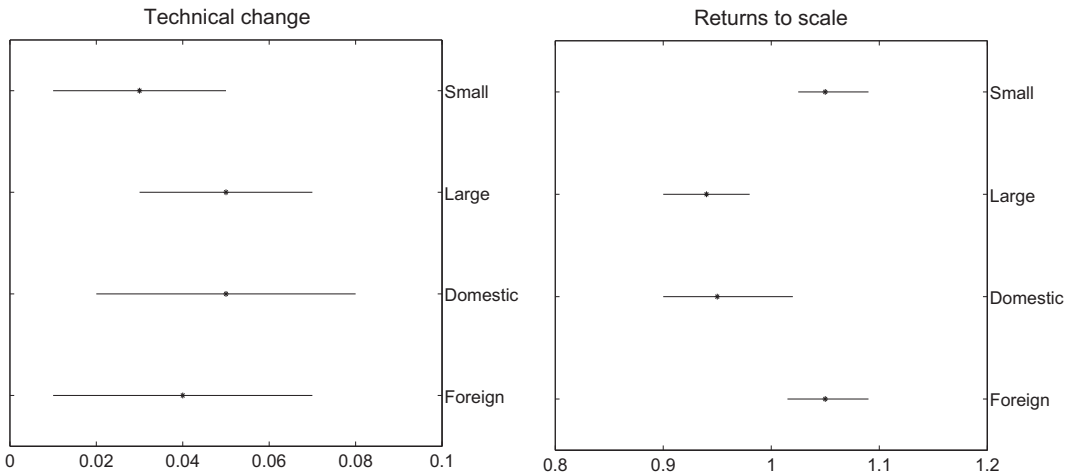

Fig. 5. 95% probability intervals of technical change and returns to scale by groups of banks. Note: 95% probability density intervals of average posterior distributions of TC and RTS for each group of banks. These are the average of the values for each bank evaluated at every iteration of the MCMC. If the intervals do not overlap each other, the estimates of technical change and RTS for one group are different from the other with probability greater than 95%. In the case of TC, if the intervals do not contain 0, then we can conclude in favor of technical change with a probability greater than 95%. In particular, from Eq. (7), $TC > 0$ implies technical progress and $TC < 0$ implies technical regress. In the case of RTS, if the intervals do not contain 1, we can conclude following Eq. (6) in favor of DRS ($RTS < 1$) or IRS ($RTS > 1$) with a probability greater than 95%.

Table 4
Posterior mean and 95% probability intervals of the inefficiency parameter distributions in random coefficients models; sub-sample periods 2002–2007 and 2008–2012.

	Model C3a		Model C3b		Model P3a		Model P3b	
	2002–2007		2008–2012		2002–2007		2008–2012	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	0.726*	[0.255,1.049]	0.795*	[0.279,1.149]	−1.222*	[−1.425,−1.018]	−1.254*	[−1.462,−1.045]
γ_1 *size*	−0.272*	[−0.501,−0.043]	−0.321*	[−0.590,−0.051]	0.484*	[0.409,0.558]	0.683*	[0.578,0.787]
γ_2 *foreign*	−0.826*	[−1.308,−0.345]	−0.984*	[−1.558,−0.411]	0.457*	[0.189,0.724]	0.521*	[0.216,0.826]
γ_1^* *credit*	0.683*	[0.258,1.107]	0.789*	[0.298,1.279]	−1.572*	[−2.654,−0.791]	−1.344*	[−2.439,−0.248]
γ_2^* *liquidity*	0.719*	[0.009,1.409]	0.836*	[0.011,1.636]	0.941*	[0.115,1.767]	0.737*	[0.090,1.385]
γ_3^* *capital*	−2.346*	[−3.251,−1.072]	−1.892*	[−2.623,−0.865]	−1.819*	[−2.437,−1.201]	−1.464*	[−2.261,−0.667]
γ_4^* *market*	−0.217*	[−0.367,−0.067]	−0.116*	[−0.196,−0.036]	−1.100*	[−1.929,−0.471]	−1.004*	[−1.759,−0.429]
Mean eff.		0.845		0.763		0.652		0.711
SD eff.		0.122		0.155		0.180		0.224
DIC_3		1362.23		1361.40		1766.36		1765.45
LPS		−112.04		−112.69		−417.97		−421.90

Note: Values for γ_1^* to γ_4^* correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC.
Negative coefficients imply a positive effects on efficiency and the opposite is true for positive coefficients.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

of credit risk on cost and profit efficiency for small banks is significantly greater during 2008–2012 than in the period 2002–2007. Likewise, the positive effect of capital on both types of efficiency is lower after 2008 for small banks. In contrast, the magnitude of these effects on the efficiency of large banks remain unaltered. The fact that only small banks increased their costs associated to similar levels of credit risk and diminished their benefits associated to capitalisation after 2008, may suggest that large Colombian banks were either more prepared to operate under a less favorable environment and more strict regulation or that large banks were more confident in receiving public support in case of being needed.

6.2. Non-performing loans

In our estimations, we use an ex-ante measure of credit risk based on loan ratings. However, most of studies use NPL as a measure of credit risk. NPL are an ex-post measure of this type of risk since they account for unpaid loans and risk is already materialized. Nevertheless, differences in the way NPL affect efficiency of banks with different characteristics have been found previously. Kwan and Eisenbeis (1997) find negative effects on efficiency of large banks but positive effects for small banks in

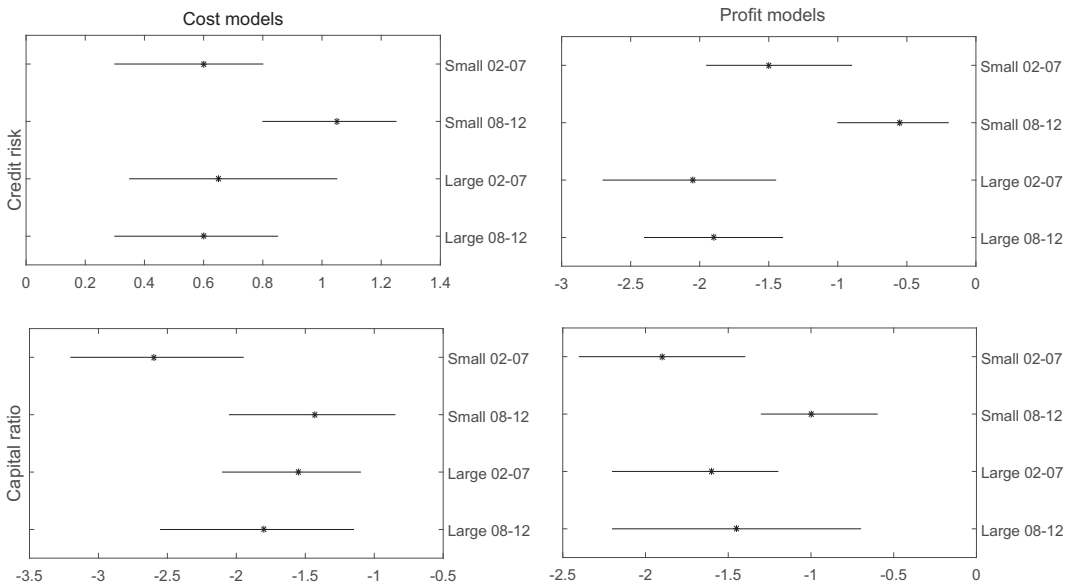

Fig. 6. Probability intervals of credit risk and capital: small vs large banks, 2002–2007 and 2008–2012. Note: 95% probability density intervals of average posterior distributions of the random inefficiency coefficients for each group of banks. These are the average of the values for each bank-specific parameter at every iteration of the MCMC. If the intervals do not overlap each other, the posterior estimates for one group are different from the other with probability greater than 95%. If the interval do not contain the value of 0, risk affects efficiency of that group of banks with a probability greater than 95%. Negative values imply a positive effect of risk on efficiency and positive values imply a negative effect of risk on efficiency.

Table 5
Posterior mean and 95% probability intervals of the inefficiency parameter distributions in random coefficients models using NPL.

	Model C7		Model P7		Model C8		Model P8	
	NPL		NPL		ROA		ROA	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
γ_0	0.987*	[0.371,1.543]	−1.498*	[−1.915,−1.013]	0.455*	[0.159,0.658]	−1.136*	[−1.325,−0.947]
γ_1 *size*	−0.312*	[−0.503,−0.107]	0.602*	[0.427,0.795]	−0.192*	[−0.366,−0.017]	0.575*	[0.487,0.663]
γ_2 *foreign*	−1.003*	[−1.355,−0.648]	0.615*	[0.292,0.958]	−1.005*	[−1.615,−0.594]	0.459*	[0.190,0.728]
γ_1^* *credit*					0.643*	[0.087,1.164]	−1.281*	[−2.325,−0.237]
γ_2^* *liquidity*	0.762*	[0.054,1.463]	0.801*	[0.054,1.593]	0.742*	[0.009,1.452]	0.804*	[0.098,1.509]
γ_3^* *capital*	−1.948*	[−2.737,−0.971]	−1.694*	[−2.265,−1.186]	−1.931*	[−2.676,−0.882]	−1.552*	[−2.079,−1.025]
γ_4^* *market*	−0.195*	[−0.369,−0.026]	−1.014*	[−1.691,−0.233]	−0.245*	[−0.415,−0.076]	−0.944*	[−1.655,−0.404]
γ_5^* *NPL*	0.657*	[0.191,0.997]	−0.124	[−0.411,0.231]				
γ_6^* *ROA*					−1.388*	[−2.505,−0.270]	0.042	[−0.665,0.749]
Mean eff.		0.784		0.671		0.812		0.705
SD eff.		0.144		0.195		0.182		0.201
DIC_3		1419.51		1811.90		1353.83		1876.19
LPS		−105.46		−331.85		−116.04		−351.62

Note: NPL are included as the ratio of non-performing to total loans in the previous period.
Note: Values for γ_1^* to γ_4^* correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC.
Negative coefficients imply a positive effects on efficiency and the opposite is true for positive coefficients.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

the US. Thus, we assess the effects on the estimations of using NPL as credit risk measure and whether the ex-ante measure proposed provides additional information and improves estimations. Table 5 presents the posterior estimations for the cost and profit efficiency random coefficients models using NPL. Results suggest that NPL affects negatively cost efficiency, as found when the ex-ante credit risk measure was used. In this case, unpaid loans generate costs derived from negotiating workout arrangements, disposing more collateral for other potential problem loans or defending bank's safety. However, the model using NPL exhibit lower fit and predictive performance, suggesting that the ex-ante variable may provide more reliable estimations. Regarding the profit model, NPL shows no effect on efficiency. This is opposite to the results obtained using the ex-ante measure, which identifies the incentives generated from the risk-return relationship. Hence, fit and predictive performance indicators are poorer when NPL is used and profit efficiency estimations are underestimated (see Malikov et al., 2015, for evidence on biased efficiency estimations when ex-post measures of credit risk are used). From the regulatory perspective, this result is also important given that Colombian banks are required to set their provisions for loan losses according to their risky loans level. As a result, ex-ante credit risk measures may capture better risk-taking incentives of banks and provide regulators with a more suitable indicator for setting bank provisions for loan losses.

6.3. Alternative inefficiency distributions and covariates

In the literature previous studies include profitability as an inefficiency driver as well as estimate both gamma and exponential distributions for the inefficiency component (Tabak and Tecles, 2010; Tecles and Tabak, 2010). Accordingly, we include ROA as an explanatory covariate in the inefficiency distribution of both cost and profit models in order to asses whether profitability has an influence along with risk in explaining efficiency. We find that ROA has a statistically significant effect in the cost model (C8), while in the profit model (P8) it has no significant effect. This result indicates, on the one hand, that more profitable banks are more cost efficient, while ROA differences are not relevant as profit efficiency drivers. Interestingly, we find that the impact of ROA in cost efficiency increases the dispersion of efficiency estimates and also mean cost efficiency increases from 0.77 (baseline model) to 0.81 (see Table 5).

Finally, we estimate all cost and profit models using a gamma distribution instead of an exponential distribution as described in Section 3.3.[27] Table A.4 and Fig. A2 in the Appendix show the posterior estimation for the inefficiency parameters and plot the posterior efficiency distributions, respectively. We find that results of the estimated coefficients remain regardless of the use of an alternative distribution indicating their robustness. However, we observe that dispersion of efficiency estimates increases with gamma distribution and also we identify lower efficiency levels, especially in the profit models.

7. Concluding remarks

Risk-taking is an inherent condition of the banking business. However, traditional studies on bank efficiency have assumed that risk is incorporated into bank output without explicitly modeling its role in explaining efficiency. Recent studies show that

[27] We perform a similar exercise to that in Tabak and Tecles (2010) and Tecles and Tabak (2010) following the priors structure in Griffin and Steel (2007).

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, omitting other important risks faced by banks.

We present a stochastic frontier model with random inefficiency coefficients, which captures unobserved heterogeneity related to credit, liquidity, capital, and market risk exposures. The model is found to accurately distinguish heterogeneous responses to changes in risk exposures among banks and provides the first empirical evidence on the role of risk-taking in the efficiency of the Colombian banking sector. 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; Hou et al., 2014; Pessarossi and Weill, 2015). Cost and profit efficiency are found to be over-/ underestimated when risk measures are not properly modeled into the profit and cost functions. We also find that size and foreign ownership are not only important determinants of efficiency but also key characteristics determining the way changes in risk exposures affect bank efficiency. The main channels supporting these differences among banks are related to monitoring costs, diversification, information asymmetries, agency costs, and risk-taking incentives.

In particular, we find that higher credit risk exposures lead to lower cost efficiency, which 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. Further, we identify that an ex-ante measure of credit risk captures better risk-taking incentives of banks than an ex-post measure such as NPL, and may provide regulators with a more suitable indicator for setting bank provisions for loan losses. The decreasing trend on credit risk exposures of Colombian banks, even during a period of large credit expansion and high economic growth, may be related with the use of this measure for regulatory purposes.

Our results provide evidence to support the hypothesis that capital requirements may contribute to enhance banking efficiency (Naceur and Omran, 2011; Chortareas et al., 2012; Barth et al., 2013; Pessarossi and Weill, 2015). We identify that higher capitalisation 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. However, we find that those marginal benefits from capitalisation 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 financial regulator. This finding may imply that the positive effect of capitalisation on the incentives of shareholders and managers to be more efficient can be limited when the cost of raising capital increases. On the contrary, holding liquid assets seems to be costless for banks and to reduce banks's returns as liquidity was found to have negative effects on both cost and profit efficiency.

Our results also suggest positive effects of market risk on 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 from the expertise of their foreign parents, more diversified portfolios and access to cheaper funding sources (Lensink et al., 2008; Chen and Liao, 2011). 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. However, as large and foreign banks tend to rely more on unstable sources of funding (i.e. money markets) and to exhibit more market-based-income it can leads to financial fragility and enhances systemic risk (Brunnermeier et al., 2012; Laeven et al., 2016).

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). In particular, after 2008 small banks experienced an increase in the cost associated with credit risk exposures and a decrease in the benefits obtained from capitalisation over efficiency. This result may suggests that large banks were either more prepared to operate under a less favorable environment and more strict regulation or that large banks were more confident in receiving public support in case of being needed. Moreover, the fact that large banks face lower costs and present incentives to take on more risk in credit and securities markets constitutes a signal for regulators to closely monitor the behavior of these type of banks and their potential accumulation of risk (Hou et al., 2014). 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 measures that account for risk-taking constitute a useful indicator for financial stability considerations in emerging markets given that banks with lower efficiency have been found to be more prone to future bank fails and tend to engage on more risk (Tabak et al., 2011). Regulators should be aware not only of the consequences of prudential regulation on bank performance, but also of the different effects that polices intended to discourage risk exposure have on banks with different characteristics related to size and affiliation.

Acknowledgements

We acknowledge Harry Huizinga and Wolf Wagner for their guidance and suggestions. We are grateful with Subal Kumbhakar, Mike Tsionas, Benjamin Tabak, two anonymous reviewers and the Editors (Linda Allen and Jonathan Batten) for their useful comments. We also thank the participants of the Central Bank Research Joint Seminar on Monetary Policy and Financial

Stability (CEMLA), the 51th Eastern Finance Association Meeting, and the Banco de la República Seminar for their helpful comments.

Appendix A

Table A.1
Summary statistics by groups of banks.

Variable	Mean	Median	SD	Min	Max
Small banks ($n = 416$)					
Total loans	985,515	826,879	667,003	9383	2,696,732
Securities	379,716	256,449	344,862	204	1,393,741
OBS	0.0471	0.0374	0.0397	0.0001	0.2650
Price of deposits	0.0079	0.0075	0.0028	0.0004	0.0254
Price of labor	10.5659	8.4528	7.3962	1.3291	66.7323
Price of capital	0.5895	0.2764	1.0177	0.0029	8.8976
Total assets	1,619,551	1,235,202	1,115,449	52,309	3,545,718
Credit risk exposure	0.1170	0.0882	0.0882	0.0037	0.4740
Liquidity ratio	0.2090	0.1860	0.1180	0.0214	0.5800
Capital ratio	0.1320	0.1080	0.0747	0.0623	0.4970
Market risk exposure	0.2190	0.1990	0.1470	0.0005	0.7650
Total cost	105,691	85,114	76,139	5946	491,070
Total profit	1002	−1920	22,485	−108,206	77,188
Large banks ($n = 432$)					
Total loans	5,346,787	3,451,866	4,503,450	758,826	28,267,020
Securities	2,045,615	1,775,987	1,272,240	334,376	6,666,803
OBS	0.0408	0.0325	0.0313	0.0001	0.2150
Price of deposits	0.0053	0.0052	0.0021	0.0009	0.0118
Price of labor	7.6186	7.2293	2.8862	0.0499	18.2958
Price of capital	0.3754	0.2797	0.2997	0.0058	2.8417
Total assets	8,837,084	6,195,099	6,581,894	3,547,137	41,786,468
Credit risk exposure	0.1040	0.0861	0.0596	0.0342	0.3670
Liquidity ratio	0.2310	0.2190	0.0819	0.0328	0.4900
Capital ratio	0.1010	0.0981	0.0280	0.0448	0.1780
Market risk exposure	0.2600	0.2340	0.1160	0.0725	0.5580
Total cost	478,765	292,534	465,953	50,346	3,546,014
Total profit	38,381	5984	135,260	− 261,771	756,685
Domestic banks ($n = 547$)					
Total loans	3,983,266	2,399,882	4,399,050	11,552	28,267,020
Securities	1,519,082	1,059,576	1,387,424	204	6,666,803
OBS	0.0451	0.0357	0.0353	0.0001	0.2650
Price of deposits	0.0060	0.0060	0.0025	0.0004	0.0186
Price of labor	6.8401	6.5064	2.4024	0.0499	17.6841
Price of capital	0.3693	0.2525	0.5344	0.0058	8.8976
Total assets	6,560,745	4,256,538	6,675,098	116,867	41,786,468
Credit risk exposure	0.1220	0.0944	0.0799	0.0072	0.4740
Liquidity ratio	0.2120	0.2000	0.0901	0.0214	0.5800
Capital ratio	0.1100	0.0994	0.0545	0.0448	0.4750
Market risk exposure	0.2320	0.2120	0.1190	0.0005	0.5580
Total cost	348,859	198,416	440,633	15,837	3,546,014
Total profit	33,628	1687	120,780	−261,771	756,685
Foreign banks ($n = 301$)					
Total loans	1,797,142	1,038,357	2,208,175	9383	11,322,972
Securities	700,101	464,628	716,145	795	2,776,628
OBS	0.0418	0.0318	0.0367	0.0001	0.2150
Price of deposits	0.0076	0.0073	0.0030	0.0021	0.0254
Price of labor	13.1796	11.3445	7.5630	1.3291	66.7323
Price of capital	0.6840	0.4032	1.0065	0.0029	7.5630
Total assets	2,998,759	2,101,320	3,384,305	52,309	16,983,860
Credit risk exposure	0.0895	0.0767	0.0606	0.0037	0.3210
Liquidity ratio	0.2360	0.2130	0.1190	0.0328	0.5770
Capital ratio	0.1290	0.1120	0.0624	0.0553	0.4970
Market risk exposure	0.2530	0.2290	0.1570	0.0068	0.7650
Total cost	199,230	119,698	224,506	5946	1,533,103
Total profit	−4642	−1940	21,740	−96,572	55,599

Source: Colombian Central Bank and FSC.
All monetary values are expressed in thousands of U.S. dollars at constant prices of 2012.

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

	Model C1		Model C2		Model C3		Model C4	
	No risk		Fixed risk coefficients		Random risk coefficients		Risk in frontier	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
β_0	5.0904*	[4.011,6.296]	5.2911*	[4.426,6.188]	4.8096*	[3.691,6.065]	5.5647*	[4.498,6.603]
β_1	0.0373*	[0.002,0.097]	0.0207*	[0.003,0.043]	0.0611*	[0.003,0.123]	0.0922*	[0.039,0.132]
β_2	0.0649*	[0.001,0.152]	0.0554*	[0.005,0.152]	0.0281*	[0.001,0.076]	0.0697*	[0.006,0.175]
β_3	0.0333*	[0.001,0.083]	0.0361*	[0.003,0.077]	0.0400*	[0.002,0.127]	0.0221*	[0.001,0.052]
β_{11}	0.0427*	[0.012,0.077]	0.0468*	[0.018,0.077]	0.0524	[−0.002,0.096]	0.0743*	[0.044,0.104]
β_{12}	0.0149	[−0.03,0.055]	0.0095	[−0.031,0.048]	0.0017	[−0.056,0.067]	−0.0602*	[−0.106,−0.014]
β_{13}	−0.0039	[−0.009,0.000]	−0.0035	[−0.008,0.001]	−0.0023	[−0.008,0.003]	−0.0011	[−0.005,0.003]
β_{22}	0.0093	[−0.028,0.047]	0.0126	[−0.021,0.046]	0.0026	[−0.060,0.056]	0.0974*	[0.046,0,147]
β_{23}	0.0014	[−0.002,0.004]	0.0012	[−0.001,0.004]	0.0010	[−0.002,0.004]	−0.0011	[−0.004,0.002]
β_{33}	0.0009*	[0.000,0.002]	0.0008	[−0.001,0.002]	0.0011	[−0.000,0.003]	0.0004	[−0.001,0.002]
δ_1	0.0618*	[0.002,0.174]	0.0594*	[0.004,0.143]	0.0384*	[0.001,0.114]	0.0976*	[0.002,0.206]
δ_2	0.0721*	[0.003,0.247]	0.0690*	[0.005,0.164]	0.0606 *	[0.002,0.189]	0.0450*	[0.002,0.099]
δ_{11}	0.0878*	[0.034,0.129]	0.0746*	[0.023,0.115]	0.0159	[−0.063,0.087]	0.0542	[−0.006,0.102]
δ_{12}	−0.0885*	[−0.12,−0.052]	−0.0825*	[−0.111,−0.052]	−0.0587*	[−0.102,−0.014]	−0.0660*	[−0.099,−0.031]
δ_{22}	0.0804*	[0.039,0.120]	0.0743*	[0.039,0.109]	0.0732 *	[0.030,0.113]	0.0482*	[0.007,0.089]
η_{11}	0.0829*	[0.055,0.11]	0.0821*	[0.057,0.106]	0.0893*	[0.048,0.128]	0.0771*	[0.049,0.104]
η_{12}	−0.0164	[−0.042,0.008]	−0.0159	[−0.037,0.006]	−0.0195	[−0.051,0.015]	−0.0119	[−0.034,0.010]
η_{21}	−0.0096	[−0.041,0.014]	−0.0156	[−0.047,0.009]	−0.0539*	[−0.094,−0.013]	−0.0260	[−0.053,0.000]
η_{22}	−0.0460*	[−0.070,−0.017]	−0.0414*	[−0.064,−0.018]	−0.0241	[−0.055,0.007]	−0.0286*	[−0.052,−0.005]
η_{31}	0.0007	[−0.003,0.005]	0.0009	[−0.002,0.004]	0.0018	[−0.002,0.006]	0.0004	[−0.003,0.004]
η_{32}	0.0019	[−0.002,0.006]	0.0012	[−0.002,0.005]	−0.0009	[−0.006,0.003]	0.0026	[−0.001,0.006]
κ_1	−0.1037*	[−0.178,−0.027]	−0.1077*	[−0.170,−0.045]	−0.0928*	[−0.158,−0.03]	−0.1086*	[−0.172,−0.045]
κ_2	0.0007	[−0.002,0.003]	0.0007	[−0.002,0.003]	0.0015	[−0.001,0.004]	−0.0002	[−0.003,0.002]
ϕ_1	0.0109*	[0.004,0.018]	0.0112*	[0.006,0.017]	0.0109*	[0.006,0.017]	0.0107*	[0.005,0.017]
ϕ_2	−0.0103*	[−0.015,−0.003]	−0.0105*	[−0.015,−0.006]	−0.0108*	[−0.015,−0.006]	−0.0090*	[−0.014,−0.005]
ϕ_3	0.0001	[−0.000,0.000]	0.0000	[−0.000,0.000]	−0.0002	[−0.000,0.000]	0.0000	[−0.000,0.000]
φ_1	−0.0120*	[−0.02,−0.003]	−0.0125*	[−0.020,−0.006]	−0.0116*	[−0.02,−0.004]	−0.0127*	[−0.021,−0.005]
φ_2	0.0050	[−0.002,0.012]	0.0050	[−0.001,0.011]	0.0030	[−0.003,0.009]	0.0032	[−0.003,0.01]
ω_1							0.0538	[−0.221,0.334]
ω_2							−0.0755	[−0.236,0.086]
ω_3							0.2936	[−0.043,0.614]
ω_4							−0.4360	[−0.848,0.000]
DIC_3		2237.07		1812.33		1359.87		2119.65
LPS		−12.03		−76.96		−114.74		−20.10

Estimations for the frontier parameters derived from the profit efficiency models.
In Model C4, risk covariates are included in the frontier and not in the inefficiency component.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

Table A.3
Posterior mean and 95% probability intervals of the frontier parameter distributions in profit models.

	Model P1		Model P2		Model P3		Model P4	
	No risk covariates		Fixed risk coefficients		Random risk coefficients		Risk in frontier	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
β_0	8.8101	[−1.462,16.767]	3.3282	[−4.316,13.527]	6.4845*	[1.579,12.170]	8.8857	[−2.738,15.876]
β_1	2.1175*	[0.456,3.637]	2.8217*	[1.147,4.327]	2.0398*	[0.869,2.997]	2.4465*	[0.884,3.889]
β_2	2.3737*	[1.126,3.735]	3.2102*	[1.989,4.350]	2.4766*	[1.705,3.224]	2.8854*	[1.617,4.030]
β_3	−0.1391	[−0.274,0.009]	−0.1828	[−0.305,0.045]	−0.1485	[−0.237,0.054]	−0.1523	[−0.293,0.021]
β_{11}	−0.2742*	[−0.428,−0.121]	−0.3065*	[−0.465,−0.151]	−0.2395*	[−0.350,−0.103]	−0.3395*	[−0.464,−0.181]
β_{12}	0.2138*	[0.058,0.367]	0.2456*	[0.074,0.412]	0.1850*	[0.042,0.310]	0.3075*	[0.151,0.446]
β_{13}	0.0139*	[0.002,0.026]	0.0122*	[0.003,0.022]	0.0102*	[0.002,0.018]	0.0141*	[0.001,0.026]
β_{22}	0.0083	[−0.086,0.117]	0.0231	[−0.086,0.146]	0.0381	[−0.057,0.156]	−0.0622	[−0.158,0.065]
β_{23}	−0.0027	[−0.015,0.010]	−0.0009	[−0.010,0.008]	0.0009	[−0.004,0.006]	−0.0040	[−0.012,0.003]
β_{33}	0.0005	[−0.002,0.003]	0.0008	[−0.002,0.003]	−0.0011	[−0.003,0.000]	0.0013	[−0.002,0.005]
δ_1	−0.6712	[−1.923,0.939]	−1.7524*	[−2.989,−0.338]	−1.3228*	[−2.137,−0.449]	−1.1864	[−2.644,0.022]
δ_2	0.3282	[−0.692,1.218]	0.9088	[−0.098,1.680]	0.6580	[−0.156,1.159]	0.6532	[−0.246,1.611]
δ_{11}	0.0716	[−0.056,0.228]	−0.0117	[−0.120,0.106]	−0.0174	[−0.101,0.068]	0.0410	[−0.060,0.169]
δ_{12}	−0.0003	[−0.149,0.127]	0.0380	[−0.073,0.132]	0.0332	[−0.030,0.094]	0.0176	[−0.103,0.112]
δ_{22}	−0.0307	[−0.177,0.137]	−0.0600	[−0.168,0.071]	−0.0817*	[−0.152,−0.012]	−0.0696	[−0.195,0.089]
η_{11}	0.0937	[−0.061,0.229]	0.1752*	[0.008,0.301]	0.1294*	[0.040,0.217]	0.1346*	[0.007,0.273]
η_{12}	0.0676	[−0.039,0.175]	0.0200	[−0.079,0.123]	0.0610	[−0.005,0.124]	0.0349	[−0.075,0.130]
η_{21}	0.0028	[−0.063,0.077]	−0.0243	[−0.085,0.041]	−0.0164	[−0.059,0.024]	−0.0023	[−0.063,0.053]

(*continued on next page*)

Table A.3 (*continued*)

	Model P1		Model P2		Model P3		Model P4	
	No risk covariates		Fixed risk coefficients		Random risk coefficients		Risk in frontier	
	Mean	95% PI	Mean	95% PI	Mean	95% PI	Mean	95% PI
η_{22}	−0.0680	[−0.150,0.004]	−0.0498	[−0.114,0.015]	−0.0625*	[−0.103,−0.019]	−0.0520	[−0.123,0.016]
η_{31}	−0.0048	[−0.016,0.009]	−0.0086	[−0.018,0.003]	−0.0050	[−0.011,0.002]	−0.0065	[−0.020,0.005]
η_{32}	−0.0030	[−0.013,0.007]	0.0022	[−0.008,0.011]	−0.0018	[−0.008,0.004]	0.0003	[−0.009,0.013]
κ_1	−0.1007	[−0.305,0.123]	−0.1629	[−0.329,0.005]	−0.1532*	[−0.255,−0.051]	−0.1089	[−0.282,0.065]
κ_2	0.0020	[−0.004,0.008]	−0.0016	[−0.006,0.003]	−0.0003	[−0.003,0.003]	0.0009	[−0.004,0.007]
ϕ_1	0.0197*	[0.003,0.036]	0.0248*	[0.010,0.038]	0.0233*	[0.013,0.033]	0.0176*	[0.001,0.033]
ϕ_2	−0.0068	[−0.017,0.004]	−0.0067	[−0.015,0.003]	−0.0091*	[−0.015,−0.003]	−0.0049	[−0.014,0.006]
ϕ_3	−0.0009	[−0.002,0.000]	−0.0007	[−0.002,0.000]	−0.0005	[−0.001,0.000]	−0.0008	[−0.002,0.000]
φ_1	0.0146	[−0.006,0.038]	0.0131	[−0.003,0.030]	0.0072	[−0.002,0.017]	0.0101	[−0.007,0.031]
φ_2	−0.0162	[−0.041,0.009]	−0.0157	[−0.032,0.002]	−0.0131*	[−0.022,−0.004]	−0.0140	[−0.034,0.003]
ω_1							−0.3028	[−0.802,0.209]
ω_2							−0.4596	[−0.777,0.128]
ω_3							−0.1873	[−0.764,0.454]
ω_4							0.0495	[−0.666,0.755]
DIC_3		2534.41		1843.58		1763.09		2329.63
LPS		−198.01		−362.90		−424.47		−254.82

Notes: Estimations for the frontier parameters derived from the profit efficiency models.
In Model P4, risk covariates are included in the frontier and not in the inefficiency component.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

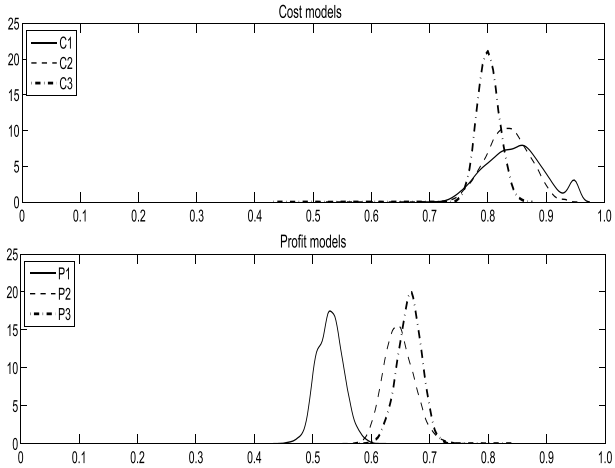

Fig. A1. Predictive distributions of efficiency under cost and profit models. This figure depicts differences in the predictive efficiency distributions of cost and profit models. Models with no risk-taking covariates (C1 and P1), models with common risk coefficients (C2 and P2) and models with random risk coefficients (C3 and P3).

Table A.4
Posterior mean and 95% probability intervals of the inefficiency parameter distributions in random coefficients models using a gamma distribution.

	Model C9		Model P9	
	Mean	95% PI	Mean	95% PI
γ_0	0.8134*	[0.2987,1.1363]	−1.1934*	[−1.3516,−1.0540]
γ_1 *size*	−0.2435*	[−0.4523,−0.0908]	0.5279*	[0.4115,0.6473]
γ_2 *foreign*	−1.2539*	[−1.7284,−0.7192]	0.6326*	[0.3510,0.8854]
γ_1^* *credit*	0.6952*	[0.3090,0.9516]	−1.3147*	[−2.0682,−0.6348]
γ_2^* *liquidity*	0.8351*	[0.0192,1.4572]	0.8135*	[0.1693,1.4256]
γ_3^* *capital*	−1.9360*	[−2.6157,−1.3745]	−1.6518*	[−2.0719,−1.1425]
γ_4^* *market*	−0.2075*	[−0.4136,−0.0351]	−0.9872*	[−1.7015,−0.5160]
Mean eff.		0.7244		0.6376
SD eff.		0.1625		0.2331
DIC_3		1350.24		1791.37
LPS		−116.78		−418.52

Note: Values for γ_1^* to γ_4^* correspond to the average posterior distribution of individual coefficients, which is the average of the values for each bank-specific parameter at every iteration of the MCMC.
Negative coefficients imply positive effects on efficiency and the opposite is true for positive coefficients.
* indicates that the estimated parameter is different from 0 with a probability greater than 95%.

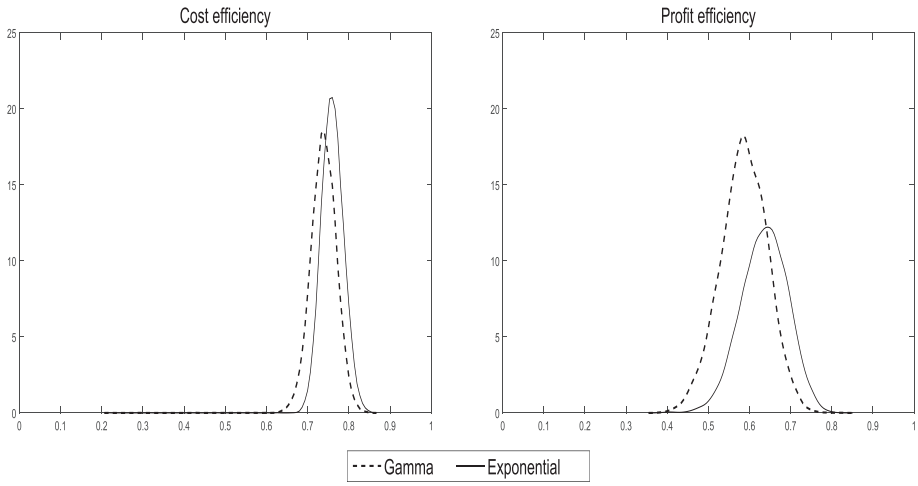

Fig. A2. Posterior cost and profit efficiency distributions — gamma vs. exponential inefficiency distributions. Note: Comparison of posterior efficiency distributions using specifications for Models C3 and P3 and the inefficiency prior distributions as described in Section 3.3.

References

Agoraki, M., Delis, M., Pasiouras, F., 2011. Regulations, competition and bank risk-taking in transition countries. J. Financ. Stab. 7, 38–48.

Aigner, D., Lovell, C., Schmidt, P., 1977. Formulation and estimation of stochastic frontier production function models. J. Econ. 6, 21–37.

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

Angelini, P., Nobili, A., Picillo, A., 2011. The interbank market after August 2007: what has changed and why? J. Money, Credit, Bank. 43 (5), 923–958.

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

Barajas, A., Steiner, R., Salazar, A., 2002. The impact of liberalization and foreign direct investment in Colombia's financial sector. J. Dev. Econ. 23, 157–196.

Barth, J., Lin, C., Ma, Y., Seade, J., Song, F., 2013. Do bank regulation, supervision and monitoring enhance or impede bank efficiency? J. Bank. Financ. 37, 2879–2892.

Beccalli, E., Anolli, M., Borello, G., 2015. Are European banks too big? Evidence on economies of scale. J. Bank. Financ. 58, 232–246.

Beltratti, A., Stulz, R.M., 2012. The credit crisis around the globe: why did some banks perform better? J. Financ. Econ. 105, 1–17.

Berger, A., Bowman, C., 2013. How does capital affect bank performance during financial crises? J. Financ. Econ. 109, 146–176.

Berger, A., DeYoung, R., 1997. Problem loans and cost efficiency in commercial banks. J. Bank. Financ. 21 (6), 849–870.

Berger, A., Mester, L., 1997. Inside the black box: what explains differences in the efficiencies of financial institutions? J. Bank. Financ. 21, 895–947.

Bertay, A., Demirgüç-Kunt, A., Huizinga, H., 2013. Do we need big banks? Evidence on performance, strategy and market discipline. J. Financ. Intermed. 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.

BIS, 2013. Basel III: the liquidity coverage ratio and liquidity risk monitoring tools. Basel Committee on Banking Supervision June. Bank for International Settlements.

Bitar, M., Saad, W., Benlemlih, M., 2016. Bank risk and performance in the MENA region: the importance of capital requirements. Econ. Syst. 40, 398–421.

Bos, J., Koetter, M., Kolari, J., Kool, C., 2009. Effects of heterogeneity on bank efficiency scores. Eur. J. Oper. Res. 195, 251–261.

Bos, J., Kool, C., 2006. Bank efficiency: the role of bank strategy and local market conditions. J. Bank. Financ. 30, 1953–1974.

Boyd, J., De Nicoló, G., 2005. The theory of bank risk taking and competition revisited. J. Financ. 60, 1329–1343.

Brunnermeier, M., Dong, G., Palia, D., 2012. Banks Non-Interest Income and Systemic Risk. Princeton University., pp. 44.

Brunnermeier, M., Pedersen, L., 2009. Market liquidity and funding liquidity. Rev. Financ. Stud. 22 (6), 2201–2238.

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

Celeux, G., Forbes, F., Robert, C., Titterington, D., 2006. Deviance information criteria for missing data models. Bayesian Anal. 4, 651–674.

Chen, S., Liao, C., 2011. Are foreign banks more profitable than domestic banks? Home- and host-country effects of banking market structure, governance, and supervision. J. Bank. Financ. 35, 819–839.

Chortareas, G., Girardone, C., Ventouri, A., 2012. Bank supervision, regulation, and efficiency: evidence from the European Union. J. Financ. Stab. 8, 292–302.

Clavijo, S., Rojas, C., Salamanca, C., Montoya, G., Rizo, C., 2006. Mergers and acquisitions in the Colombian financial sector: impact on efficiency (1990–2005). Icfai J.Mergers Acquis. 3, 38–61.

Curi, C., Lozano-Vivas, A., Zelenyuk, V., 2015. Foreign bank diversification and efficiency prior to and during the financial crisis: does one business model fit all? J. Bank. Financ. 61, 522–535.

Daude, C., Pascal, J., 2015. Efficiency and contestability in the Colombian banking system. OECD Economics Department Working Papers, No. 1203. OECD.

Davies, R., Tracey, B., 2014. Too big to be efficient? The impact of implicit subsidies on estimates of scale economies for banks. J. Money, Credit, Bank. 46, 219–253.

De Jonghe, O., Disli, M., Schoors, K., 2012. Corporate governance, opaque bank activities, band risk/return efficiency: pre- and post-crisis evidence from Turkey. J. Financ. Serv. Res. 41, 51–80.

Estrada, D., Osorio, P., 2004. Efectos del capital financiero en la eficiencia del sistema bancario Colombiano. Ensayos Sobre Polí,tica Económica 47, 62–201.

Feng, G., Zhang, X., 2012. Productivity and efficiency at large and community banks in the US: a Bayesian true random effects stochastic distance frontier analysis. J. Bank. Financ. 36, 1883–1895.

Fiordelisi, F., Marques-Ibanez, D., Molyneux, P., 2011. Efficiency and risk in European banking. J. Bank. Financ. 35, 1315–1326.

Flannery, M., 2010. Market discipline in bank supervision. The Oxford Handbook of Banking. Oxford University Press, Inc.
Fries, S., Taci, A., 2005. Cost efficiency of banks in transition: evidence from 289 banks in 15 post-communist countries. J. Bank. Financ. 29, 55–81.
Galán, J., Veiga, H., Wiper, M., 2014. Bayesian estimation of inefficiency heterogeneity in stochastic frontier models. J. Prod. Anal. 42, 85–101.
Galán, J., Veiga, H., Wiper, M., 2015. Dynamic effects in inefficiency: evidence from the Colombian banking sector. Eur. J. Oper. Res. 240, 562–571.
Goddard, J., Molyneux, P., Williams, J., 2014. Dealing with cross-firm heterogeneity in bank efficiency estimates: some evidence from Latin America. J. Bank. Financ. 40, 130–142.
Gómez, E., Lizarazo, A., Mendoza, J., Murcia, A., 2016. Evaluating the Impact of Macroprudential Policies in Colombia. mimeo. Banco De La República.
Gomez-Gonzalez, J.E., Kiefer, N., 2009. Bank failure: Evidence from the Colombian financial crisis. Int. J. Bus. Financ. Res. 3, 15–31.
Good, I., 1952. Rational decisions. J. R. Stat. Soc. B 14, 107–114.
Greene, W., 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. J. Econ. 126, 269–303.
Griffin, J., Steel, M., 2004. Semiparametric Bayesian inference for stochastic frontier models. J. Econ. 123, 121–152.
Griffin, J., Steel, M., 2007. Bayesian stochastic frontier analysis using WinBUGS. J. Prod. Anal. 27, 163–176.
Handorf, W., 2014. The cost of bank liquidity. J. Bank. Regul. 15, 1–13.
Hou, X., Wang, Q., Li, C., 2015. Role of off-balance sheet operations on bank scale economies: evidence from China's banking sector. Emerg. Mark. Rev. 22, 140–153.
Hou, X., Wang, Q., Zhang, Q., 2014. Market structure, risk taking, and the efficiency of Chinese commercial banks. Emerg. Mark. Rev. 20, 75–88.
Hughes, J., Mester, L., 1993. A quality and risk-adjusted cost function for banks: evidence on the too-big-to-fail doctrine. J. Prod. Anal. 4 (3), 293–315.
Hughes, J., Mester, L., 1998. Bank capitalization and cost: evidence of scale economies in risk management and signaling. Rev. Econ. Stat. 80 (2), 314–325.
Hughes, J., Mester, L., 2010. Efficiency in banking. The Oxford Handbook of Banking. Oxford University Press, Inc..,
Hughes, J., Mester, L., 2013. Who said large banks don't experience scale economies? Evidence from a risk-return-driven cost function. J. Financ. Intermed. 22 (4), 559–585.
Hughes, J., Mester, L., Moon, C., 2001. Are scale economies in banking elusive or illusive?: Evidence obtained by incorporating capital structure and risk-taking into models of bank production. J. Bank. Financ. 25 (12), 2169–2208.
Ioannidou, M., Penas, M., 2010. Deposit insurance and bank risk-taking: evidence from internal loan ratings. J. Financ. Intermed. 19, 95–115.
Kirkpatrick, C., Murinde, V., Tefula, M., 2008. The measurement and determinants of X-efficiency in commercial banks in Sub-Saharan Africa. Eur. J. Financ. 14, 625–639.
Koetter, M., 2008. The stability of efficiency rankings when risk-preferences and objectives are different. Eur. J. Financ. 14 (2), 115–135.
Koop, G., Steel, M., Osiewalski, J., 1995. Posterior analysis of stochastic frontier models using Gibbs sampling. Comput. Stat. 10, 353–373.
Kwan, S., Eisenbeis, R., 1997. Bank risk, capitalization and operating efficiency. J. Financ. Serv. Res. 12 (2), 117–131.
Laeven, L., Levine, R., 2009. Bank governance, regulation and risk taking. J. Financ. Econ. 93, 259–275.
Laeven, L., Ratnovski, L., Tong, H., 2016. Bank size, capital and systemic risk: some international evidence. J. Bank. Financ. 69, 525–534.
Lensink, R., Meesters, A., Naaborg, I., 2008. Bank efficiency and foreign ownership: do good institutions matter? J. Bank. Financ. 32, 834–844.
León, C., Machado, C., Cepeda, F., Sarmiento, M., 2012. Systemic risk in large value payment systems in Colombia: a network topology and payments simulation approach. In: Hellqvist, M., Laine, T. (Eds.), Diagnostics for the Financial Markets — Computational Studies of Payment System, Simulator Seminar Proceedings, 2009–2011. Bank of Finland.
López, M., Tenjo, F., Zrate, H., 2014. Credit cycles, credit risk and countercyclical loan provisions. Ensayos sobre Poltica Económica 32, 9–17.
Lozano-Vivas, A., Pasiouras, F., 2014. Bank productivity change and off-balance-sheet activities across different levels of economic development. J. Financ. Serv. Res. 46, 271–294.
Malikov, E., Restrepo-Tobón, D., Kumbhakar, S., 2015. Estimation of banking technology under credit uncertainty. Empir. Econ. 49, 1185–1211.
Meeusen, W., van den Broeck, J., 1977. Efficiency estimation from Cobb-Douglas production functions with composed errors. Int. Econ. Rev. 8, 435–444.
Moreno, D., Estrada, D., 2013. Colombian bank efficiency and the role of market structure. Temas De Estabilidad Financiera, No. 76. Banco De La República.,
Naceur, S., Omran, M., 2011. The effects of bank regulations, competition, and financial reforms on banks' performance. Emerg. Mark. Rev. 12, 1–20.
Pessarossi, P., Weill, L., 2015. Do capital requirements affect cost efficiency? Evidence from China. J. Financ. Stab. 19, 119–127.
Podpiera, J., Weill, L., 2008. Bad luck or bad management? Emerging banking market experience. J. Financ. Stab. 4 (2), 135–148.
Radić, N., Fiordelisi, F., Girardone, C., 2012. Efficiency and risk-taking in pre-crisis investment banks. J. Financ. Serv. Res. 41 (1), 81–101.
Santos, J., 2014. Evidence from the bond market on banks' "too big to fail" subsidy. Econ. Policy Rev. 20 (2), 29–39.
Sarmiento, M., 2016. Market Discipline and Liquidity Risk: Evidence from the Interbank Funds Market. Mimeo. Graduate Institute Geneva.
Sarmiento, M., Cepeda, A., Mutis, H., Perez, J., 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.
Sarmiento, M., Leon, C., Cely, J., 2017. An early warning indicator system to monitor the unsecured interbank funds market. Res. Int. Bus. Financ. 40, 114–128.
Sealey, C., Lindley, J., 1977. Inputs, outputs and a theory of production and cost at depository financial institutions. J. Financ. 32, 1252–1266.
Shleifer, A., Vishny, R., 2010. Unstable banking. J. Financ. Econ. 97 (3), 306–318.
Spiegelhalter, D., Best, N., Carlin, B., van der Linde, A., 2002. Bayesian measures of model complexity and fit. J. R. Stat. Soc. 64 (4), 583–616.
Sturm, J., Williams, B., 2008. Characteristics determining the efficiency of foreign banks in Australia. J. Bank. Financ. 32, 2346–2360.
Tabak, B., Craveiro, G., Cajueiro, D., 2011. Bank efficiency and default in Brazil: causality tests. Working Paper Series, No. 235. . Central Bank of Brazil.,
Tabak, B., Fazio, D., Cajueiro, D., 2013. Systemically important banks and financial stability: the case of Latin America. J. Bank. Financ. 37, 3855–3866.
Tabak, B., Tecles, P., 2010. Estimating a Bayesian stochastic frontier for the Indian banking system. Int. J. Prod. Econ. 125, 96–110.
Tecles, P., Tabak, B., 2010. Determinants of bank efficiency: the case of Brazil. Eur. J. Oper. Res. 207, 1587–1598.
Uribe, J., Vargas, H., 2002. Financial reform, crisis and consolidation in Colombia. Borradores De Economía, No. 204. Banco De La República.
van den Broeck, J., Koop, G., Osiewalski, J., Steel, M., 1994. Stochastic frontier models: a Bayesian perspective. J. Econ. 61, 273–303.
Wagner, W., 2010. Loan market competition and bank risk-taking. J. Financ. Serv. Res. 37, 71–81.
Wang, H., Schmidt, P., 2002. One step and two step estimation of the effects of exogenous variables on technical efficiency levels. J. Prod. Anal. 18, 129–144.
Wheelock, D.C., Wilson, P.W., 2012. Do large banks have lower costs? New estimates of returns to scale for U.S. banks. J. Money Credit Bank. 44 (1), 171–199.
Williams, J., 2004. Determining management behaviour in European banking. J. Bank. Financ. 28, 2427–2460.
Williams, J., 2012. Efficiency and market power in Latin American banking. J. Financ. Stab. 8, 263–276.