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BAYESIAN ANALYSIS OF DYNAMIC EFFECTS IN INEFFICIENCY: EVIDENCE FROM THE COLOMBIAN BANKING SECTOR

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Abstract

Firms face a continuous process of technological and environmental changes that implies making managerial decisions in a dynamic context. However, costs and other constraints prevent firms from making instant adjustments towards optimal conditions and may cause inefficiency to be persistent in time. In this work, we propose a flexible dynamic model that makes possible to distinguish persistent effects in the inefficiency from firm inefficiency heterogeneity and to capture differences in the adjustment costs between firms. The new model is fitted to a ten year sample of Colombian banks. Our findings suggest that firm characteristics associated to size and foreign ownership have negative effects on inefficiency and separating these heterogeneity factors from the dynamics of inefficiency improves model fit. On the other hand, acquisitions are found to have positive and persistent effects on inefficiency. Colombian banks are found to present high inefficiency persistence but there exist important differences between institutions. In particular, merged banks present low costs of adjustment that allow them to recover rapidly the efficiency losses derived from merging processes.

Keywords: Banks Efficiency; Bayesian Inference; Dynamic Effects; Persistent Shocks; Heterogeneity; Stochastic Frontier Models.
JEL classification: C11; C22; C23; C51; D24; G21

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I. Introduction

The decision making process followed by producers is dynamic in nature. Technology and environment change continuously and variations with respect to their current production conditions have to be considered by firms. However, firms face restrictions and costs in the adjustment process. Regulation, quasi-fixed and indivisible inputs, and transaction, information and other adjustment costs are important factors preventing firms from making free and instant adjustments towards optimal conditions. In this context, firms may not only be inefficient at some point, but this inefficiency may persist from one period to the next, and firms may find it optimal to remain partly inefficient in the short-run.

This issue has been little studied in the efficiency measurement literature but has recently become an important concern. In stochastic frontier models, first introduced by Aigner et al. (1977) and Meeusen and van den Broeck (1977), we can find two alternative approaches to deal with time dependent inefficiencies. The first approach defines deterministic time specifications for the evolution of efficiency. As examples we find the proposals by Kumbhakar (1990) and Battese and Coelli (1992) where a time invariant inefficiency measure is multiplied by a parametric function of time, the model by Cornwell et al. (1990) that defines producer specific parameters, and the proposal by Lee and Schmidt (1993) where time dummies are used. These models have the problem of imposing arbitrary restrictions on the short-run efficiency and are not able to model firm-level dynamic behaviour.

The second, more recent approach considers the dynamic behaviour of inefficiency. These models try to estimate long-run efficiency by recognizing a persistence effect of firms' inefficiency over time. This is achieved by modeling the evolution of firm inefficiency as an autoregressive process. In this context, Ahn et al. (2000) defined an error structure intended to capture the relationship between the short and long-run dynamics. This pioneer proposal has been criticized for its economic foundations and for modeling autoregressive processes on nonnegative variables. A second proposal that avoids this problem and argues that improvements on technical efficiency depend on the costs of adjustment was introduced by Tsionas (2006). This inefficiency specification implies that the one-sided error follows a log-normal distribution where the mean presents an autoregressive structure and the variance is equal to that of random shocks. The model can be specified in a state-space form and following this idea Emvalomatis et al. (2011) proposed an alternative approach where the ratio of efficiency to inefficiency follows an autoregressive process and uses Kalman filtering techniques to derive the likelihood.

The models by Tsionas (2006) and Emvalomatis et al. (2011) assume a constant persistent effect for all firms in the sector. However, firms may face different costs of adjustment. Large firms may benefit from economies of scale to adapt faster to new technologies while foreign firms may incur in lower costs to adapt their processes to new regulations or to certain shocks given more diversification or cheaper access to multiple sources of funding (see Chen and Liao, 2011). Heterogeneity of inefficiency persistence was found to be significant by Huang and Chen (2009) in an application to French banks using an extension of the proposal by Ahn et al. (2000) that considers rational expectations. There the homogeneous persistence restriction was found to lead to biased estimators and underestimation of technical efficiency. Firm specific adjustment costs can be tested rather than imposed in dynamic specifications.

Modeling heterogeneity is another important issue that may avoid potential biases in inefficiency estimations. In this regard, Emvalomatis (2012) extended the Emvalomatis et al. (2011) model to account for unobserved technological heterogeneity through a random effects specification. Findings show that it is important to separate heterogeneity sources from inefficiency dynamics in order to get unbiased estimators. On the other hand, Tsionas (2006) allows the inclusion of heterogeneity in the inefficiency rather than in the frontier. In this specification, observed covariates are modeled into the dynamics of the inefficiency implying that they have persistent effects over time.

Inefficiency covariates may include heterogeneity variables capturing firm specific characteristics or observed shocks capturing changes in particular conditions. In the first case, covariates are intended to model attributes inherent to each bank, such as the type ownership, that differentiate them in terms of the efficiency level but not necessarily imply persistent effects or adjustment costs. On the other hand, changes in these characteristics or observed shocks, such as acquisition processes, may imply adjustments to the new conditions, costs associated to this process, and thus persistent effects on inefficiency.

In this work we propose a flexible model that separates observed bank specific characteristics from the inefficiency dynamics but allows for modeling shocks with persistent effects on the inefficiency. The model also accounts for heterogeneous adjustment costs between firms. This specification allows to model persistent and non persistent effects on the inefficiency and to identify potential differences in the costs of adjustment between banks. In particular, we analyze our model under a Bayesian framework and compare it to that of Tsionas (2006).

Regarding the functional form, we use an input distance function, which have the advantage of considering input quantities instead of prices. This avoids the problem of using firm specific prices that do not fulfill the competitive input prices assumption (see Berger and Mester, 2003). Another advantage of using distance functions is that they are able to deal with multiple outputs in contrast to production functions. In the dynamic efficiency literature to the best of our knowledge, the only study using a distance function is that by Emvalomatis et al. (2011) in an application to dairy farms. Thus, this is the first study using a dynamic input distance function to evaluate efficiency of the banking sector.

We apply the new specification to a sample of Colombian banks during the last decade. In this period, the banking sector in Colombia presented important changes in terms of mergers, arrival of new competitors and an environment of rapid growth of foreign capital. In particular, we identify the effects of size, foreign ownership, and mergers and acquisitions on the evolution of efficiency. In previous studies, these characteristics have been found to have important effects on inefficiency. Recently, Tabak and Tecles (2010) found size to be a determinant of cost efficiency in India, Assaf et al. (2013) identified important differences in efficiency between foreign and domestic banks in Turkey and Cuesta and Orea (2002), in a study of Spanish bank mergers, found negative impacts on output efficiency after merger processes are carried out followed by rapid recoveries after some periods. Regarding the effects of mergers, results from a dynamic flexible model using an input distance function are interesting since these effects are considered to be more relevant on revenue and profit efficiency as found by Akhavein et al. (1997) for US merged institutions. In fact, most of previous studies using static models have found none or very little improvement on input or costs efficiency for merged banks (see Amel et al., 2004, for a review on the effects of mergers over efficiency in the financial sector of developed countries).

We also analyze economies of scale and technical changes and validate whether the high persistence effect found by Tsionas (2006) in US banks is also a characteristic of the banking sector of an emerging economy. In particular, regarding previous studies for the Colombian banking sector, this is the first work involving a distance function, using Bayesian inference and analyzing the effects of mergers and acquisitions carried out between 2005 and 2008.

The rest of the paper contains four additional sections. In Section 2, we describe the characteristics of the distance function. In Section 3, we present the dynamic specification proposed for the inefficiency. In Section 4, we show how to carry Bayesian inference for this model and a model comparison criterion. In Section 5, we describe characteristics of the Colombian banking sector and present the results of the empirical application. Section 6 concludes the study.

II. Stochastic input distance functions

We assume that banks employ an $N \times 1$ vector of inputs $\mathbf{x} = (x_1, x_2, \ldots, x_N)'$ to provide an $M \times 1$ vector of service outputs $\mathbf{q} = (q_1, q_2, \ldots, q_M)'$. We also define the following input set:

$$L_g(q) = \mathbf{x} : \mathbf{x}\,\text{and technology}\; g\,\text{can produce}\;\mathbf{q}, \tag{1}$$

where the technology g satisfies the axioms of closeness, boundedness, strong disposability and convexity as described by Färe and Primont (1995). Based on the input set, it is possible to define the following input distance function that describes the regular technology g:

$$D_I(\mathbf{x}, \mathbf{q}, g) = \sup_{\lambda}\{\lambda : \mathbf{x}/\lambda \in L_g(\mathbf{q}) \geq 1, \tag{2}$$

where λ denotes the maximum amount by which an input vector can be radially contracted while the output vector remains constant. We assume that in each period all banks use the best available technology. So, for bank i in period t, the Debreu-Farrell input-oriented measure of technical efficiency (TE) is:

$$TE(x_{it}, q_{it}, t) \equiv 1/D_I(x_{it}, q_{it}, t). \tag{3}$$

The input distance function is homogeneous of degree one, a non-decreasing concave function of inputs and a non-increasing quasi-concave function of outputs (see Färe and Primont, 1995). Linear homogeneity implies that it is possible to normalize all the inputs in the distance function by an arbitrarily chosen input $x_{N_{it}}$:

$$1/x_{N_{it}} = D_I(x_{it}/x_{N_{it}}, q_{it}, t)\exp(-u_{it}), \tag{4}$$

where $u_{it} \equiv \ln D_I(x_{it}/x_{N_{it}}, q_{it}, t) \geq 0$. So, a bank is technically efficient if and only if $u_{it} = 0$ or similarly, $TE(x_{it}, q_{it}, t) = 1$.

Regarding the technology representation, we use a translog functional form in order to parameterize the distance function. So, we define $v_{it} \equiv \ln D_I(x_{it}/x_{N_{it}}, q_{it}, t) - TL(x_{it}/x_{N_{it}}, q_{it}, t)$, where $TL(.)$ is the translog function. Then, (4) becomes:

$$y_{it} = TL(x_{it}/x_{N_{it}}, q_{it}, t) + v_{it} - u_{it}, \tag{5}$$

where $y_{it} \equiv -\ln x_{N_{it}}$. If any outputs or normalized inputs are stochastic then v_{it} is stochastic and (5) becomes a standard translog stochastic frontier model. For the estimation, the inefficiency term u_{it} is assumed to follow a nonnegative distribution and the random noise component v_{it} is assumed to follow a normal distribution.

From (5), technical efficiency of individual firms in each period is calculated as:

$$TE_{it} = \exp(-u_{it}). \tag{6}$$

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

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

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

Finally, technical change (TC) measuring common shifts in the input distance function is given by:

$$TC = \left(\frac{\partial \ln D_I(\mathbf{x}, \mathbf{y}, t)}{\partial t}\right). \tag{8}$$

III. Dynamic stochastic frontier models

The dynamic stochastic frontier model proposed by Tsionas (2006) is the following;

$$\begin{aligned} y_{it} = &\quad \mathbf{x_{it}}\boldsymbol{\beta} + v_{it} - u_{it}, && v_{it} \sim N(0, \sigma_v^2) \\ \log\ u_{it} = &\quad \mathbf{z_{it}}\boldsymbol{\gamma} + \rho\ \log\ u_{i,t-1} + \xi_{it}, && \xi_{it} \sim N(0, \sigma_\xi^2) \\ \log\ u_{i1} = &\quad \mathbf{z_{i1}}\boldsymbol{\gamma}/(1-\rho) + \xi_{i1}, && \xi_{i1} \sim N(0, \sigma_\xi^2/(1-\rho^2)) \end{aligned} \tag{9}$$

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 latter is a function of a row vector of covariates $\mathbf{z_{it}}$, a vector of parameters $\boldsymbol{\gamma}$, the persistence parameter ρ, and a normally distributed error term ξ_{it} which is assumed to capture random shocks in the short-run.

The model assumes a first order autoregressive process for the logarithm of the inefficiencies, which intends to capture the part of the inefficiency which is transmitted from one period to the next. This persistence parameter measures the effect of the costs of adjustment faced by the firms in the sector, which avoids to correct the factors causing the inefficiency in the short-run. The parameter ρ is in absolute value strictly smaller than 1 to assure stationarity of the process. This parameter is common to all firms, which implies that all firms face the same adjustment costs. In this proposal, observed covariates are allowed to be modeled into the inefficiency through the vector $\mathbf{z_{it}}$ and enter directly into the dynamic of the inefficiency. This implies that firm attributes may have a persistent effect on the inefficiency equal to that of other common unobserved factors.

A more recent dynamic model proposed by Emvalomatis et al. (2011) employed a variation of (9) where rather than the inefficiency itself, a ratio of technical efficiency to inefficiency follows an autoregressive process. In this model, persistence is also treated as constant for all firms and inefficiency covariates are not considered. This implies that the long-run expected value for technical efficiency tends to a common constant for all firms in the sector and may misidentify firm heterogeneity with inefficiency. In fact, in an extension of this model, Emvalomatis (2012) found that unobserved frontier heterogeneity can be interpreted as inefficiency if it is not accounted for. All these studies use a dynamic specification typical in unobserved components models that can be represented in terms of a state space model. The main difference is that Emvalomatis et al. (2011) use maximum likelihood techniques to estimate the model and the Kalman-filter to filter the efficiency while Tsionas (2006) and Emvalomatis (2012) use Bayesian inference.

A. Separating heterogeneity and modeling firm-specific persistence

To include firm characteristics in the inefficiency component is important to distinguish properly heterogeneity from inefficiency. These covariates capture specific characteristics that are inherent to firms and distinguish them from each other. However, they do not necessarily imply adjustment processes and persistent effects on inefficiency. Moreover, if they are allowed to be persistent and everything remains constant, they may define a trend in the evolution of inefficiency over time. This would imply that a firm with certain characteristic may not only present less inefficiency than other in every observed period but also that it will improve its efficiency over time due to that characteristic. These differences in the evolution of efficiency between firms can be related to differences on adjustment costs and then they can be directly captured by allowing firm specific persistence parameters. On the other hand, observed shocks that change operating conditions of firms may imply adjustment costs and therefore persistent effects on inefficiency over time. As consequence, these shocks should be modeled in the persistent component of the inefficiency.

Thus, we propose a model that allows separating persistent and non-persistent components on the inefficiency. The former include observed shocks capturing changes in conditions that imply adjustment costs and the latter include certain firm specific characteristics inherent to firms. Moreover, the model allows the persistent component of the inefficiency to change between firms recognizing that it is possible for banks to face different costs of adjustment. In fact, heterogeneous persistence across firms was a significative pattern in the French banking sector as was found out by Huang and Chen (2009) using a modification of the model by Ahn et al. (2000). This implies to model a flexible firm specific persistent component in the inefficiency.

The following is the proposed general dynamic model that allows us to account for all these conditions:

$$y_{it} = \mathbf{x_{it}}\boldsymbol{\beta} + v_{it} - u_{it}, \qquad v_{it} \sim N(0, \sigma_v^2) \tag{10}$$

$$\log u_{it} = \theta_{it} + \mathbf{z_{it}}\boldsymbol{\gamma} + \xi_{it}, \qquad \xi_{it} \sim N(0, \sigma_\xi^2) \tag{11}$$

$$\theta_{it} = \omega + \mathbf{s_{it}}\boldsymbol{\psi} + \rho_i\, \theta_{i,t-1} + \eta_{it}, \quad \eta_{it} \sim N(0, \sigma_\eta^2), \qquad t = 2...T \tag{12}$$

$$\theta_{i1} = \frac{\omega + \mathbf{s_{i1}}\boldsymbol{\psi}}{1-\rho_i} + \eta_{i1}, \qquad \eta_{i1} \sim N\left(0, \frac{\sigma_\eta^2}{1-\rho_i^2}\right), \; t = 1. \tag{13}$$

The stochastic frontier is represented by (10) and (11) is the dynamic specification for the inefficiency where θ_{it} represents the persistent component that is not dependent on firm characteristics, $\mathbf{z_{it}}$ is a row vector of firm specific heterogeneity variables, $\boldsymbol{\gamma}$ is a vector of parameters and ξ_{it} is a white noise process with constant variance σ_ξ^2 which represents random shocks that are allowed to be non persistent in time.

The persistent component θ_{it} follows an autoregressive process represented by (12) where ω is a constant, $\mathbf{s_{it}}$ is a row vector of observed shocks, $\boldsymbol{\psi}$ is a vector of parameters, ρ_i is the firm specific persistence parameter measuring the proportion of the dynamic part of the inefficiency that is transmitted from one period to the next. Finally, η_{it} represents persistent random shocks that follows a normal distribution with variance σ_η^2. The process is assumed to be stationary and (13) initializes it.

Stationarity assures that the dynamics of the log-inefficiency does not diverge to negative or positive infinity. If this condition is not imposed efficiency scores could be equal to one or zero in the long-run. The first case would contradict the adjustment costs theory that motivates the dynamic formulation and the second case would imply that totally inefficient firms do not exit the market. Therefore, the persistence parameters are required to satisfy $|\rho_i| < 1$. A value close to 1 for this parameter means high persistence of the inefficiency dynamic component and slow adjustment of firms towards optimal conditions. Modeling heterogeneous persistence parameters let firms to differentiate in the way they adjust common unobserved factors and to exhibit different long-run inefficiencies.

Our model allows firms in the sector to share some common characteristics. They will have a common long-run dynamic component ω, common elasticities for the covariates and a common proportion of the dynamic part of inefficiency which is persistent in time. Finally, the firm specific persistence term ρ_i is assumed to vary around a sector mean persistence with certain variability.

The proposed dynamic specification in the system of equations from (11) to (13) encompasses other models in the literature and permits us to compare some assumptions by including restrictions. Homogeneous costs of adjustments for all banks can be studied by imposing $\rho_i = \rho$. If additionally $\xi_{it} = 0$ and $\boldsymbol{\gamma} = 0$ the model reduces to the Tsionas (2006) specification. If $\rho = 0$ the model is reduced to a static formulation with no adjustment costs but where an unobserved component θ_{it} captures latent inefficiency heterogeneity as in Galán et al. (2012). Finally, if ρ and η_{it} are equal to 0, the model takes the form of the Battese and Coelli (1995) static formulation.

It can also be noticed that if random shocks are only allowed to affect the inefficiency via the scale parameter of its distribution, then $\eta_{it} = 0$ and the inefficiency can be modeled following other nonnegative distributions with firm specific and time-varying mean.[1]

[1] However, specifying other nonnegative distributions can change the interpretation of the inefficiency parameters.

IV. Bayesian inference

Bayesian inference for stochastic frontier models was introduced by van den Broeck et al. (1994). Among its main advantages are the formal incorporation of parameter uncertainty and the derivation of posterior densities of efficiencies for every individual firm. All models derived from the general specification in (10) to (13) are fitted by Bayesian methods. We assume proper but relatively disperse prior distributions throughout. In particular, the distributions assumed for the parameters in the distance function are: $\boldsymbol{\beta} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\beta}})$ where $\boldsymbol{\Sigma}_{\boldsymbol{\beta}}^{-1}$ is a diagonal matrix with precision priors set to 0.001 for all coefficients. The variance of the idiosyncratic error term is inverse Gamma distributed, that is equivalent to $\sigma_v^{-2} \sim G(a, b)$ where the priors for shape and rate parameters are set to 0.01.

The specification in (11) can be seen as the inefficiency following a log-normal distribution. Then $u_{it}|\theta_{it}, \mathbf{z_{it}}, \boldsymbol{\gamma}, \sigma_\xi^2 \sim LN(\theta_{it} + \mathbf{z_{it}}\boldsymbol{\gamma}, \sigma_\xi^2)$, where the location component is composed of the unobserved dynamic parameter and the observed heterogeneity component. The distribution for the unobserved parameter modeling the dynamics is $\theta_{it}|\theta_{i,t-1}, \omega, \mathbf{s_{it}}, \boldsymbol{\psi}, \rho_i, \sigma_\eta^2 \sim N(\omega + \mathbf{s_{it}}\boldsymbol{\psi} + \rho_i\, \theta_{i,t-1}, \sigma_\eta^2)$ for $t = 2...T$. Given stationarity we have $\theta_{i1}|\omega, \mathbf{s_{i1}}, \boldsymbol{\psi}, \rho_i, \sigma_\eta^2 \sim N\left(\frac{\omega+\mathbf{s_{i1}}\boldsymbol{\psi}}{1-\rho_i}, \frac{\sigma_\eta^2}{1-\rho_i^2}\right)$. The distribution for the common constant ω is normal with priors set to -1.5 and 1 for the mean and precision.[2] The distribution for the persistent observed shocks parameters are: $\boldsymbol{\psi} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\psi}})$ where $\boldsymbol{\Sigma}_{\boldsymbol{\psi}}^{-1}$ is a diagonal matrix with precision priors set to 0.1. Finally, the distribution for the firm characteristic parameters in the inefficiency are: $\boldsymbol{\gamma} \sim N(\mathbf{0}, \boldsymbol{\Sigma}_{\boldsymbol{\gamma}})$ where $\boldsymbol{\Sigma}_{\boldsymbol{\gamma}}^{-1}$ is a diagonal with priors set to 0.1 for every coefficient precision.

Regarding the persistence parameters, we assume $|\rho_i| < 1$ to assure stationarity. Since the persistence parameters are allowed to vary across firms, we define a hierarchical structure where $\rho_i = 2h_i - 1$ and $h_i \sim \beta(h, 1-h)$ with $h \sim \beta(r, s)$ and priors for these parameters set to 0.5. In the case that the homogeneous persistence restriction $\rho_i = \rho$ is imposed, we define $\rho = 2h - 1$ with h defined as previously.[3] The variances are assumed to follow inverse gamma distributions where $\sigma_\eta^{-2}, \sigma_\xi^{-2} \sim G(n, d)$ with priors set to $n = 10, d = 0.01$ and $n = 1, d = 0.005$, respectively.[4]

Markov Chain Monte Carlo (MCMC) methods and in particular the Gibbs Sampling algorithm

[2]These values center the efficiency prior distributions at 0.8 similar to other Bayesian empirical applications in banking. Sensitivity analysis was performed to the prior of ω and no differences were obtained in the posterior distributions.

[3]We also studied the sensitivity to the use of a truncated normal distribution for the persistence parameters. Posterior results were found to be robust to the use of this alternative.

[4]The first was the same prior used by Tsionas (2006) for the random shocks variance in the inefficiency equation and the second was that suggested by West and Harrison (1997) for the state equation of Bayesian dynamic linear models. Sensitivity analysis was performed to these priors and posterior results were found to converge to the same values after 5.000 iterations for relative small changes and 20.000 iterations for large changes.

with data augmentation can be used here (see Koop et al., 1995, for its introduction to Bayesian inference of stochastic frontier models). The implementation of our models is carried out using the WinBUGS package (see Griffin and Steel, 2007, for a general procedure). The MCMC algorithm involved 50.000 iterations where the first 20.000 were discarded and a thinning equal to 6 was used to remove autocorrelations. So, 5.000 iterations are used for the posterior inference

As a criterion for model selection, we use a version of the Deviance Information Criterion (DIC) called DIC_3, which is calculated using the MCMC output. This 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 $\mathbf{y}$ are the data, then $DIC = 2\overline{D(\theta)} - D(\bar{\theta})$. However, using an estimator of the density $f(\mathbf{y}|\theta)$ instead of the posterior mean $\bar{\theta}$ is more stable. This alternative specification was first proposed by Richardson (2002) and presented by Celeux et al. (2006) to overcome problems when the original DIC is implemented to random effects and mixture models.[5] The formulation for this criterion is:

$$DIC_3 = -4E_\theta[\log f(\mathbf{y}|\theta)|\mathbf{y}] + 2\ \log \widehat{f}(\mathbf{y}). \tag{14}$$

V. Empirical application

A. The Colombian banking sector

The Colombian banking sector has experienced major changes in the last thirty years. It passed from a high regulated and low competitive system in the eighties to a more flexible and foreign capital open system in the nineties. From 1998 to 2002 the country suffered a deep financial crisis that lead to a rearrangement of the banking sector. This implied a reduction of the number of banks and a concentration of commercial and mortgage activities under the same institution. This reorganization process occurred during the period from 2002 to 2009, which was characterized by an environment of economic recovery, high foreign capital flows and an increase of the services provided by banks. During these years several mergers and acquisitions of banking institutions took place leading to a reduction of the number of financial institutions, which passed from more than forty mortgage and commercial banks in the mid 90's to less than twenty in 2009. Foreign capital banks had an important role in Colombia

[5] Li et al. (2012) also remark on the lack of robustness of the original DIC in models with data augmentation.

during the period of study and they accounted for almost 40% of the banking entities in 2009.

Previous efficiency studies of Colombian banking system have mainly evaluated costs and profit efficiency and have focused on the crisis and immediate post-crisis period (see Janna, 2003a, for a review on applications to the Colombian banking sector). All of these studies have shown similar results in terms of an increase in the efficiency of the sector during the mid-nineties, decreases in efficiency during the crisis period and a recovery on these indicators in the following years. The effect of banks mergers and acquisitions in Colombia has been studied by Estrada (2005) for the $1994 - 2004$ period who found gains in cost efficiency specially for low efficient pre-merged banks. Clavijo et al. (2006) study merges and acquisitions from 1990 to 2005 finding decreases in efficiency in the subsequent periods to the processes. However, most of the them occurred during the crisis period. Regarding foreign ownership, Janna (2003b) found that this variable has a negative effect on inefficiency.

B. Data and model specification

The data set contains information of twenty three commercial banks, which represents 87% of the total assets in the Colombian banking sector. This is an unbalanced panel data set of quarterly data from 2000 to 2009 from the local central bank and the supervisory agency previously studied by Cepeda et al. (2013) using non-parametric methods.[6] During the period nineteen mergers and acquisitions were carried out and we analyze these two strategic movements separately. Mergers take place between two institutions that operate in the market and they form a new institution while acquisitions involve a purchase of a bank by another and no new institutions are formed. In the sample, eight banks merged with others while three institutions were acquired by others that were not present in the Colombian banking system at that moment. Therefore, considering merged institutions as different banks, a total of thirty one banks are used for estimations. In this work, we use the intermediation approach where banks are assumed to collect deposits and other liabilities in order to transform them into earning assets. In particular, we follow the assets approach proposed by Sealey and Lindley (1977) where banks use labor, capital and deposits to produce loans, securities and other investments.[7]

We select three inputs and two outputs. Inputs are quantities of deposits (x_1), labor (x_2) and physical capital (x_3), including premises and other fixed assets. As outputs we consider the total loans

[6] Their findings suggest an increase in the overall technical efficiency of the sector and also improvements for those banks involved in merges and acquisitions.

[7] Different approaches have been found to lead to similar conclusions (see Mester, 1993).

(y_1), including consumer, industrial, commercial and real state loans; and the total investments and other securities (y_2). All monetary variables are in real terms of 2009:Q4 by deflating by the consumer price index. Regarding the inefficiency heterogeneity variables, they are the log of banks assets (z_1), its square (z_2) and foreign ownership (z_3). Public ownership is not considered since the sample contains only one bank with public capital. We include as an observed shock in the persistent component of the inefficiency, a binary variable (s_1) capturing the moment where an acquisition process was carried out. As aforementioned, merged institutions are treated as different banks.

Input x_3 is used as a numeraire to accomplish linear homogeneity in inputs and a translog input distance function derived from (5) is used. The estimated model including the dynamic specification in (11) to (13) for the inefficiency distribution is the following:

$$\begin{aligned}
-\ln x_{3_{it}} = \; & \beta_0 + \textstyle\sum_{m=1}^{2} \beta_m \ln y_{m_{it}} + \sum_{r=1}^{2} \delta_r \ln\left(\frac{x_{r_{it}}}{x_{3_{it}}}\right) + \frac{1}{2}\sum_{m=1}^{2}\sum_{n=1}^{2} \beta_{mn} \ln y_{m_{it}} \ln y_{n_{it}} \\
& + \tfrac{1}{2}\textstyle\sum_{r=1}^{2}\sum_{s=1}^{2} \delta_{rs} \ln\left(\frac{x_{r_{it}}}{x_{3_{it}}}\right) \ln\left(\frac{x_{s_{it}}}{x_{3_{it}}}\right) + \sum_{m=1}^{2}\sum_{r=1}^{2} \eta_{mr} \ln y_{m_{it}} \ln\left(\frac{x_{r_{it}}}{x_{3_{it}}}\right) \\
& + \kappa_1 t + \tfrac{1}{2}\kappa_2 t^2 + \textstyle\sum_{m=1}^{2} \phi_m t \ln y_{m_{it}} + \sum_{r=1}^{2} \varphi_r t \ln\left(\frac{x_{r_{it}}}{x_{3_{it}}}\right) - u_{it} + vit \\
& \log u_{it} = \theta_{it} + \textstyle\sum_{p=1}^{3} \gamma_p z_{p_{it}} + \xi_{it};\; \xi_{it} \sim N(0, \sigma_\xi^2) \\
& \theta_{it} = \omega + \psi s_{1_{it}} + \rho_i \theta_{i,t-1} + \eta_{it};\; \eta_{it} \sim N(0, \sigma_\eta^2);\; t = 2 \ldots T \\
& \theta_{i1} = \tfrac{\omega + \psi s_{1_{i1}}}{1-\rho_i} + \eta_{i1};\; \eta_{i1} \sim N\left(0, \tfrac{\sigma_\eta^2}{1-\rho_i^2}\right);\; t = 1.
\end{aligned} \tag{15}$$

In addition to linear homogeneity in inputs, we impose symmetry of the cross-effects by requiring $\beta_{mn} = \beta_{nm}$ and $\delta_{rs} = \delta_{sr}$.

C. Results

Using the specification in (15) we estimate four different models. Model I separates persistent components from bank specific characteristics in the inefficiency and considers heterogeneous adjustment costs but excludes observed shock variables ($\psi = 0$). Model II differs from Model I since it restricts persistence to be constant across firms. That is $\rho_i = \rho$ for all the banks. For comparison purposes we estimate Model III using the inefficiency specification in (9) proposed by Tsionas (2006). Finally, the complete model given by the system in (15) is estimated as Model IV in order to evaluate the effect of acquisitions as an observed shock variable in the persistent component of the inefficiency.

Table I presents the estimation results for the four models. In particular, in Panel C models are compared using the DIC_3 criterion where lower values indicate better fitting performance. We observe that models separating firm characteristics of size and type of ownership from the dynamics exhibit lower values for the DIC_3 criterion than the Tsionas (2006) model where they are assumed to have persistent effects. Moreover, Model I allowing for firm specific costs of adjustments exhibit the lowest value for this criterion indicating that a more flexible model regarding this parameter fits better the data.

The inefficiency coefficients of firm characteristics in Panel B suggest for all models that size has a negative impact on inefficiency but its effect is decreasing.[8] This is opposite to the findings by Tsionas (2006) for US banks. Regarding foreign ownership, the effect is also negative on the inefficiency level. This is similar to other results obtained with static models. Recently, Assaf et al. (2013) found that foreign banks are more efficient in Turkey and Claessens and Horen (2012) also presented evidence in this direction for developing countries. Beyond managerial practices, the reasons could be related to diversification or access to cheaper and multiple sources of financial resources as argued by Chen and Liao (2011).

The common persistence parameter, ρ, exhibits values very close to 1 for all the models suggesting very high persistence of the inefficiency in the Colombian banking sector. This value is very similar to that obtained by Tsionas (2006) for the case of US banks and indicates that Colombian banks also face high costs of adjustment.

In order to analyze the effects of modeling covariates out of the inefficiency dynamics we plot in Figure 1 the average posterior mean efficiencies obtained from Models II and III for foreign and domestic banks in Colombia. We can see that foreign banks present higher efficiency than domestic institutions in both models. However, the evolution is different between models. In Model II domestic and foreign banks present a stable dynamics and their efficiency estimations are close to each other at the end of the period. On the contrary, for the Tsionas (2006) model differences between foreign and domestic banks become wider over time. The reason could be due to the fact that the coefficient for this covariate parameter is negative and persistence is very high, thus when this firm characteristic is considered to have persistent effects, foreign banks present systematically higher efficiencies than in previous periods. On the other hand, in Model II any trend in the efficiency is mainly driven by the common constant

[8] In Model III the 95% credible interval for coefficients γ_1 and γ_2 are wide enough to include 0.

Table I
Posterior means of the parameter distributions

Parameters	**Model I**	**Model II**	**Model III**	**Model IV**
	$\rho_i \neq \rho$	$\rho_i = \rho$	$Tsionas$	$\rho_i \neq \rho; s_1 = acq$
Panel A: Frontier parameters				
β_0	-3.7356	-5.3883	-5.3801	-5.4800
$\beta_1(\ln y_i)$	-0.0324	-0.0044	-0.0216	-0.0409
$\beta_2(\ln y_c)$	-0.0036	-0.0029	-0.0065	-0.0220
$\beta_3(\ln dep)$	0.1065	0.0228	0.1290	0.2574
$\beta_4(\ln l)$	0.0831	0.0117	0.1029	0.0701
$\beta_5(t)$	0.0152	0.0283	0.0206	0.0105
$\beta_6(t^2)$	-0.0003	-0.0003	-0.0004	-0.0003
$\phi_1(1/2 \ln y_i^2)$	-0.0963	-0.0844	-0.0808	-0.0661
$\phi_2(\ln y_i \ln y_c)$	0.0781	0.0713	0.0734	0.0579
$\phi_3(1/2 \ln y_c^2)$	-0.1670	-0.1458	-0.1429	-0.1279
$\phi_4(1/2 \ln dep^2)$	-0.2731	-0.3098	-0.2878	-0.3479
$\phi_5(\ln dep \ln l)$	0.1480	0.1334	0.1136	0.1575
$\phi_6(1/2 \ln l^2)$	-0.1238	-0.1004	-0.0699	-0.0848
$\delta_1(\ln y_i \ln dep)$	-0.0309	-0.0296	-0.0332	-0.0213
$\delta_2(\ln y_i \ln l)$	-0.0321	-0.0187	-0.0088	-0.0181
$\delta_3(\ln y_c \ln dep)$	0.1663	0.1707	0.1530	0.1585
$\delta_4(\ln y_c \ln l)$	-0.0225	-0.0170	-0.0171	-0.0205
$\kappa_1(t \ln y_i)$	0.0023	0.0011	0.0007	0.0004
$\kappa_2(t \ln y_c)$	-0.0040	-0.0058	-0.0050	-0.0044
$\kappa_3(t \ln dep)$	0.0053	0.0092	0.0096	0.1111
$\kappa_4(t \ln l)$	-0.0029	-0.0062	-0.0068	-0.0079
σ_v^2	0.0009	0.0011	0.0012	0.0009
Panel B: Inefficiency parameters and 95% credible intervals				
ω	0.0175	0.0239	0.0002	0.0002
	[0.0163 0.0197]	[0.0168 0.0345]	[0.0001 0.0003]	[0.0001 0.0002]
$\gamma_1(\ln assets)$	-0.0407	-0.0245	-0.0001	-0.0259
	[-0.0671 -0.0192]	[-0.0049 -0.0068]	[-0.0014 0.0009]	[-0.0236 -0.0284]
$\gamma_2(\ln assets^2)$	0.0001	0.0002	0.0001	0.0002
	[0.0001 0.0002]	[0.0001 0.0002]	[-0.0001 0.0002]	[0.0001 0.0002]
$\gamma_3(foreign)$	-0.1223	-0.2061	-0.0033	-0.1232
	[-0.1587 -0.0922]	[-0.2471 -0.1594]	[-0.0048 -0.0019]	[-0.1606 -0.0865]
$\psi(acquisitions)$				0.0208
				[0.0081 0.0314]
ρ		0.9749	0.9954	
		[0.9405 0.9947]	[0.9828 0.9995]	
$\overline{\rho_i}$	0.9038			0.8943
	[0.8662 0.9518]		[0.8574 0.9291]	
σ_ξ^2	0.0003	0.0003	0.0006	0.0002
	[0.0002 0.0003]	[0.0002 0.0003]	[0.0004 0.0007]	[0.0002 0.0003]
σ_η^2	0.0001	0.0005		0.0004
	[0.0001 0.0002]	[0.0004 0.0006]		[0.0003 0.0004]
Panel C: Comparison indicators				
Mean eff.	0.4696	0.4242	0.4273	0.4420
s.d. eff.	0.1014	0.0664	0.1222	0.1035
DIC_3	-3083.7	-2949.2	-2789.6	-3126.9

persistent term regardless of the value of the covariate.

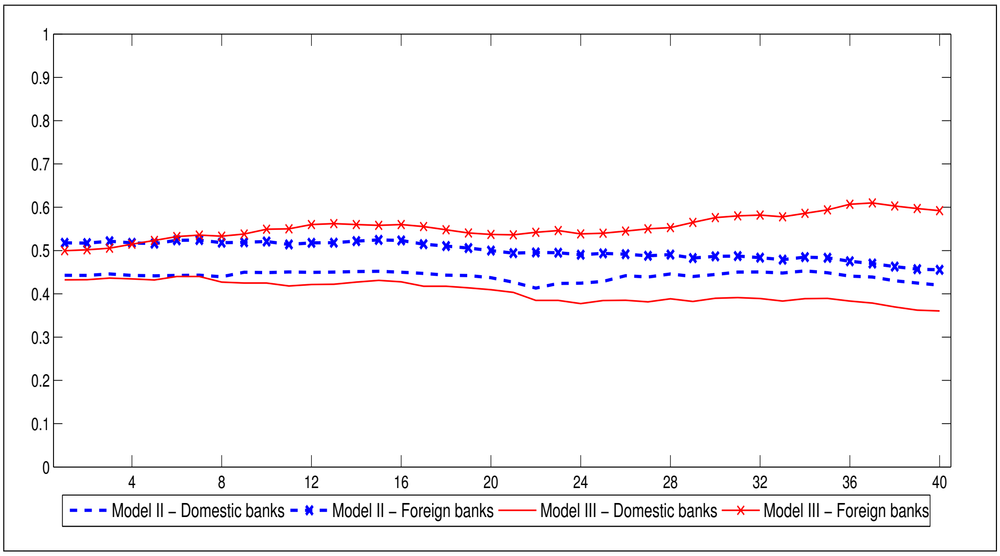


Figure 1. Evolution of mean posterior efficiencies for foreign and domestic banks

The model assuming heterogeneous adjustment costs (Model I) allows us to investigate differences in the persistence parameter between firms. Figure 2 shows the 95% credible intervals for the firm specific persistence parameters ρ_i by groups of banks. We can observe that foreign banks tend to present lower adjustment costs than other banks, although the probability of being different from the average persistence is not very high. With respect to size, large Colombian banks are more likely to present lower adjustment costs than small institutions.

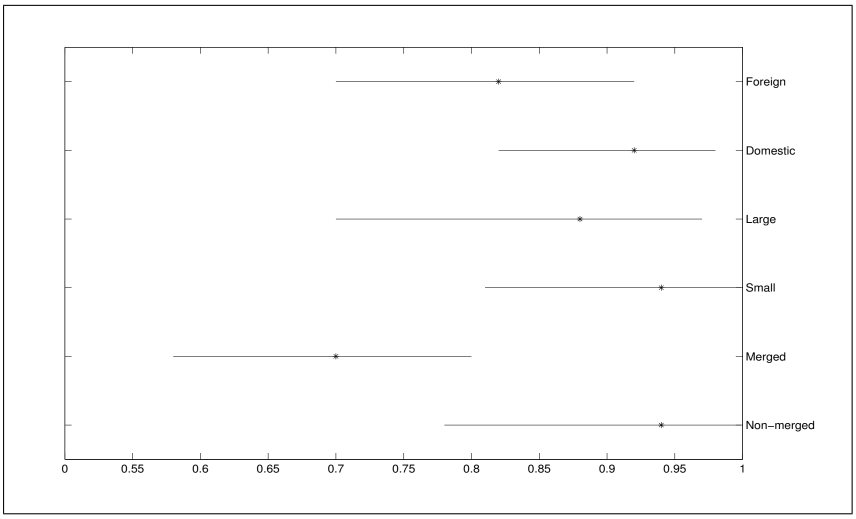


Figure 2. 95% credible intervals for firm specific persistence parameters by groups of banks

Focusing on Model I, we analyze the results obtained for efficiency, technical change and returns to scale by bank type. Table II summarizes these results. It is observed that the posterior short and long-run efficiency estimations are, in average, relatively low in all groups. This may suggest that Colombian banks operate in a low competitive sector where they may find it optimal to produce around half of the output that is technically feasible. In particular, we observe that foreign banks in Colombia present larger short and long-run efficiencies than domestic institutions. Also, technical change is larger during the last decade for foreign banks and they present increasing returns to scale. This would mean that foreign banks have more space to increase their production scale and even to think in mergers or acquisitions. In a recent study, Das and Kumbhakar (2011) found similar scale economies for foreign banks in India. On the other hand, domestic banks presented lower technical change and decreasing returns to scale that suggest that these banks should decrease their scale of operations. In this regard, it is important to notice two aspects. Firstly, most of the mergers were carried out by large domestic banks and possibly these processes increased their operations too much. Secondly, foreign banks in Colombia as in other developing countries focus on corporate customers through few branches and operations.

Table II
Short and long-run efficiencies, technical change and returns to scale by type of bank

Bank type	**SR Eff**	**LR Eff**	**TC**	**RTS**
Foreign	0.5214	0.4722	0.0315	1.1508
Domestic	0.4587	0.4051	0.0246	0.9054
Large	0.4859	0.4368	0.0292	0.9163
Small	0.4321	0.4079	0.0264	1.0257
Merged	0.4562	0.4518	0.0358	0.8752
Non-Merged	0.4910	0.4126	0.0253	1.0946

Regarding the size of the banks our study finds that it has little effect on the efficiency level. However, large banks present higher short and long-run efficiency than small banks. Technical change during the period is only a little higher for large banks than for small banks. However, large banks are found to be operating at decreasing returns to scale in opposition to small banks which are a little below the optimal scale. Most of these large banks are those involved in merges and this may suggest that these processes lead to overpass the optimal scale conditions.

C.1. Merges and acquisitions

Merges and acquisitions played and important role in the Colombian banking sector during the last decade. As aforementioned, we consider mergers as processes resulting in the creation of new institutions combining two existing banks, thus merged banks are included as new observations in the models. The evolution of the average efficiency of merged and non-merged banks is plotted in Figure 3, where results obtained from Model I assuming firm specific adjustment costs are compared to those obtained from Model II assuming homogeneous persistence.

It can be observed that efficiency of merged banks becomes lower immediately after the process is carried out. This is captured by both models. However, while Model II barely differentiates merged banks from non-merged institutions, the model with heterogeneous adjustment costs identifies a rapid recovery of the efficiency that starts around three years after the merging process and reaches the non-merged efficiency levels after five years. The reason of the differences between models is precisely the presence of heterogeneous adjustment costs between merged an non-merged institutions. In Figure 2 we can observe not only that the posterior median of the persistence parameter of merged banks is lower than that of non-merged institutions but also that the 95% credible intervals of this parameter for both groups present a very small overlap. This suggests that despite the major reorganizations and adjustments required after this process, merged banks incur in lower costs on these changes than their non-merged counterparts. This leads merged banks to present lower persistence of inefficiency over time and explains the differences in the evolution of efficiency estimations between both models.

These results are important since most of previous studies measuring input or directly cost efficiency have found none or very little evidence of improvements after merging processes (see Amel et al., 2004, for a review on studies in developed countries). The pattern on the evolution of input efficiency that we see for merged banks in Model I is similar to that identified by Cuesta and Orea (2002) in a study of output efficiency of Spanish merged banks. In that study, efficiency was found to decrease immediately after the mergers were carried out but it started to increase around six years after the process, exhibiting a concave figure. Although the model estimated by Cuesta and Orea (2002) is not dynamic in nature, it allows merged banks to follow a different temporal pattern to that of non-merged institutions. This may suggest that flexible models recognizing differences in the evolution of efficiency for merged banks are able to capture the effects of these processes.

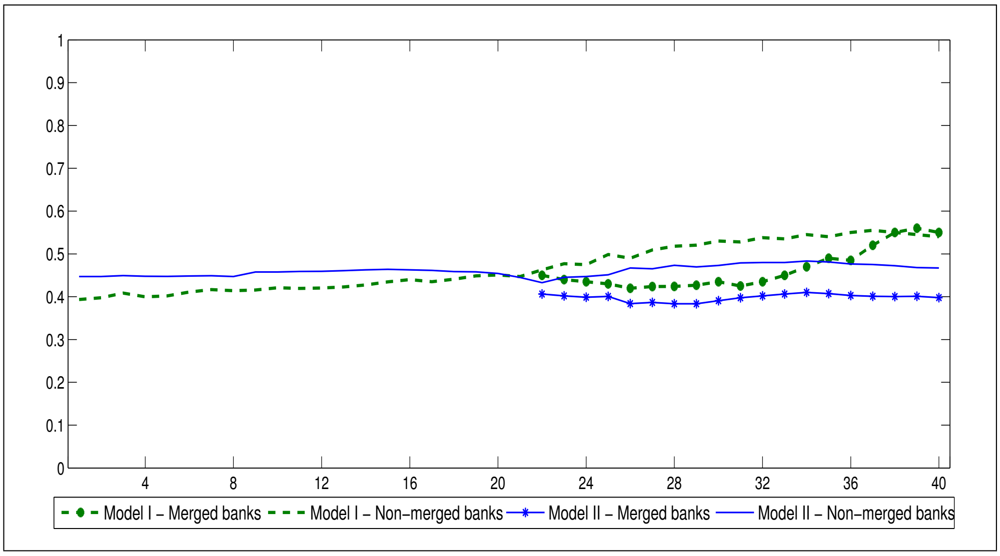
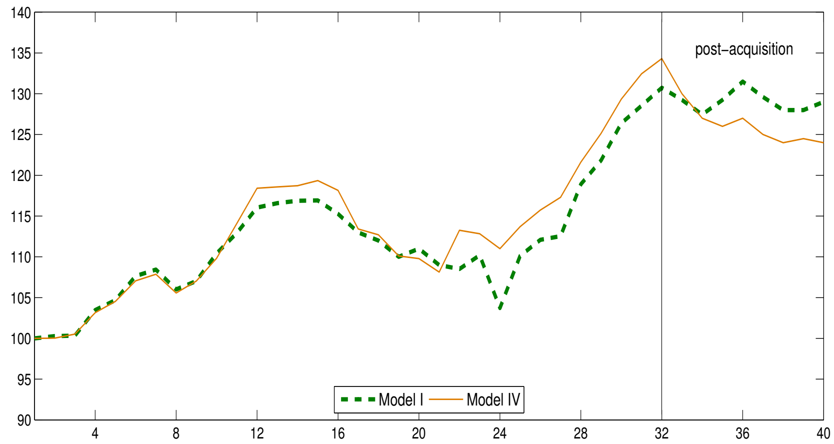


Figure 3. Evolution of mean posterior efficiencies for merged and non-merged banks

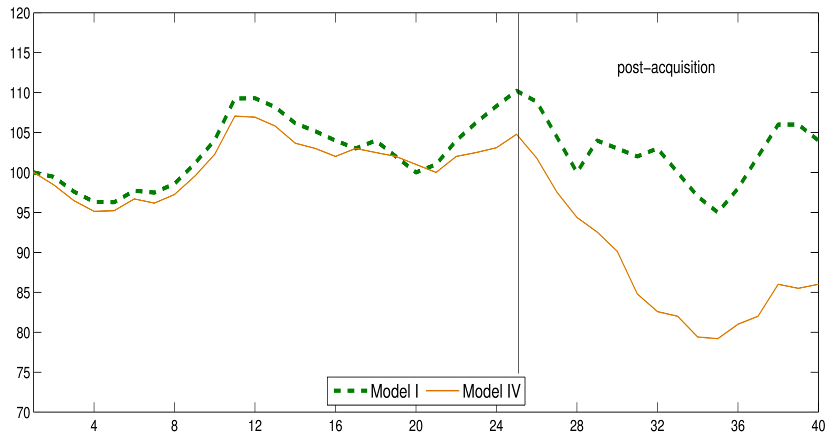
Finally, in Table II we can observe that merged banks present higher long-run efficiencies than non-merged institutions. Once more, the reason is that their costs of adjustment are much lower than those of non-merged banks and it allows them to move easier and faster towards optimal conditions. Thus, merged banks may consider optimal to reach higher efficiency levels than other institutions. Technical change is also found to be greater for merged than for non-merged banks and could be a consequence of the reorganization processes implied by mergers. However, merged banks in Colombia operate at a larger than optimal scale. This may indicate that merger processes overexpanded the size of the resulting institutions. This is opposite to non-merged institutions which still have room to increase the scale of their operations.

Regarding acquisitions, during the sample period three processes were carried out where firms that were not operating in the Colombian banking system purchased existing banks. The new ownership condition may imply adjustments in the managerial practices and can be modeled as an observed shock with persistent effects on the inefficiency. Thus, a covariate is included in the persistent component of the inefficiency in order to capture adjustment costs associated to the new condition. The estimated model (Model IV) includes a binary variable s_1 in the persistent inefficiency component of (15) that takes the value of 1 in the period where an acquisition takes place and 0 otherwise.

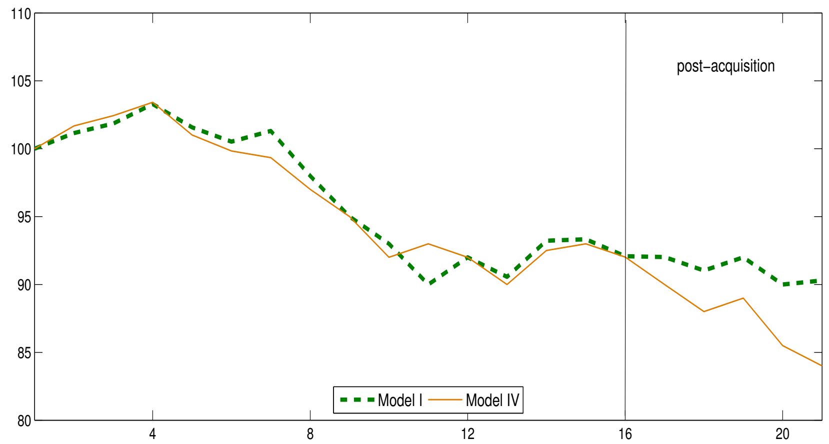
The results for Model IV presented in panels B and C of Table I exhibit a relevant positive effect of acquisitions on inefficiency and better fit performance than Model I. The posterior mean estimation



(a) Bank A



(b) Bank B



(c) Bank C

Figure 4. Evolution of index of posterior mean efficiency for acquired banks

for the acquisition coefficient suggests that these processes lead to immediate increases around 2% in the inefficiency and that their effect is persistent in time due to adjustment costs. Figure 4 shows the evolution of efficiency for the three banks in the sample that were involved in takeover processes during the period. Posterior mean efficiency estimations obtained with Models I and IV are compared in terms of an index with base equal to 100 for the first sample period.[9] It is observed that the pattern of the evolution of efficiency is similar between both models before the acquisition but differs considerably after the process is carried out for the three banks. Although, decreases in efficiency are observed immediately after the takeover process in both models, Model IV estimates larger decreases and a persistent effect over the subsequent periods. This effect must decay over time. However, since the estimated persistence parameters of acquired banks are high (above 0.9) and not very different from those of banks not involved in merges and acquisition processes, it will be only after five or six years that the effect of a takeover process would be relatively low. This behaviour is noticed for Bank B, which is the bank with the largest available data after the acquisition process. In Figure 4(b) it can be observed an increasing trend in the posterior mean efficiency after three years from the acquisition.

Overall, mergers and acquisitions have important effects on the inefficiency evolution of Colombian banks. Both strategies led to decreases of the inefficiency after the processes were carried out but efficiency levels seem to be recovered after some periods. Nevertheless, the reasons of this behaviour for merged and acquired banks are different. Merged banks present lower costs of adjustments than non-merged institutions which allows them to adjust faster, while acquired banks experiment a shock with persistent but decaying effects over the subsequent periods.

VI. Concluding remarks

In the presence of adjustment costs, firms do not find it optimal to adapt their processes towards efficiency. This behaviour is captured through a dynamic specification for the inefficiency term. One of the most relevant contributions in this context is that by Tsionas (2006) where the inefficiency is allowed to have persistent effects over time and to be driven by inefficiency covariates. In this work we extend this idea in order to distinguish dynamic persistent effects from firm specific characteristics and to recognize heterogeneity in the adjustment costs between firms. We consider that while observed shocks may have

[9] An index is used rather than efficiency scores and names of banks are omitted due to confidentiality requirements.

persistent effects on inefficiency, firm specific characteristics may affect only its level and modeling them as persistent have effects on the estimations. On the other hand, modeling inefficiency persistence as firm specific allows us to capture inefficiency heterogeneity due to differences in the adjustment costs between firms. Our models are found to fit better the data when compared to the Tsionas (2006)' specification, suggesting that bank specific characteristics related to size and type of ownership do not have persistent effects in the inefficiency. Also, allowing banks to face specific adjustment costs improves the fit performance of the model and distinguishes the evolution of efficiency between firms with different characteristics.

Bank size and foreign ownership are found to have negative effects on inefficiency in the Colombian banking sector. Large banks present higher short and long-run efficiency than small institutions. However, they are found to operate at scales larger than optimal. Small banks, on the contrary, have more room to benefit from increasing their operations. Regarding ownership, foreign institutions present higher short and long-run efficiency than domestic banks. This could be due to the fact that foreign banks are more diversified and have more funding facilities. Nevertheless, foreign banks seem to operate at suboptimal scales. In fact, foreign banks in Colombia are characterized for being specialized in corporate customers, offering more complex products and having few branches. These results suggest that they have room to expand their operating scale.

Colombian banks are also found to present very high persistence of inefficiency similar to that found by Tsionas (2006) for the US banking sector. However, important differences are observed between banks. Foreign and merged banks are found to present lower adjustment costs than domestic and non-merged institutions. This is particularly important for merged banks since this characteristic allows them to recover rapidly the efficiency losses derived from the merging processes. The lower costs of adjustment also allow merged institutions in Colombia to present higher long-run efficiencies than non-merged banks. However, they seem to operate at decreasing returns to scale. This may indicate that these banks could have overexpanded their operating scale due to the mergers. These results are opposite to those obtained for non-merged institutions, which seem to have smaller sizes than the efficient scale. Regarding acquisitions processes, they are found to have negative and persistent effects on the efficiency of acquired banks. Yet, the effect of these operations decays over time and disappear after some periods depending on the bank specific adjustment costs.

Flexible dynamic models exhibit better fit performance and captures effects that are not identified with other models. In particular, previous studies on the effects of mergers on either input or costs efficiency have not identified important improvements and it is usually attributed to the fact that revenue rather than cost efficiency is affected by mergers. Estimating the proposed model to investigate if the effects of mergers on output or revenue efficiency present similar patterns to those found in this work could be interesting for future research. Also, evaluating samples including more observed shocks and heterogeneity variables would allow to find more evidence on the effects of separating observed persistent shocks from bank specific characteristics in the inefficiency specification. Other extensions of dynamic inefficiency models such as including more heterogeneity sources or using alternative distributions for the inefficiency are also aspects of interest where work is currently in progress.

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