International Review of Economics and Finance 106 (2026) 104947

Contents lists available at ScienceDirect

International Review of Economics and Finance

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

Bank branch efficiency with a Bayesian lens on technological heterogeneity

Idaira Cabrera-Suárez [a,1], Jorge V. Pérez-Rodríguez [a], José María Pérez-Sánchez [b,*], Miguel Ángel Negrín-Hernández [a]

[a] Department of Quantitative Methods, University of Las Palmas de Gran Canaria, Spain
[b] Department of Applied Economic Analysis, University of Las Palmas de Gran Canaria, Spain

ARTICLE INFO

Keywords:
Bank branches
Output stochastic distance frontier model
Bayesian approach
Returns to scale

ABSTRACT

Although technological heterogeneity between banks has been previously considered in the literature, less attention has been given to technological heterogeneity between branches of the same bank. This paper analyses the efficiency, returns to scale (RTS) and productivity growth of bank branches considering a stochastic frontier approach that includes unobserved technological heterogeneity between branches and time-varying efficiencies. Specifically, we propose a random parameters stochastic distance frontier model that includes multiple inputs and outputs. We assume a translog output distance function estimated in an objective Bayesian framework. The empirical analysis was carried out using data from 2011 to 2017 from a large Spanish commercial bank with 122 branches. The random parameters model adds, in general, flexibility to the estimates, allowing for the identification of periods with more extreme efficiencies, both high and low, which the fixed parameters model is unable to capture. The random parameters model also detects an increase in efficiency over time that the fixed parameters model fails to identify. The differences between the two models are sufficient to drastically modify the efficiency ranking of the branches. The random parameters model also found greater dispersion than the fixed parameters model in estimation of the RTS and productivity growth.

1. Introduction

Although bank branch activities are generally homogeneous (e.g., providing similar management services for personal and business accounts and implementing policy decisions of their own bank), they can be also considered as decision-making units where managers can optimize input and output operations.

In this context, differences among bank branches may arise from both unobserved factors and technological heterogeneity. On the one hand, branches may exhibit technological disparities because they do not all operate under the same production possibility frontier. This heterogeneity can result from variations in the resources and capabilities applied to managerial practices—consistent with the resource-based view (RBV) of the firm (Wernerfelt, 1984; Barney, 1991; Conner, 1991; Peteraf, 1993). For instance, managers may adopt strategic behaviors that enable them to achieve institutional objectives (e.g., minimizing deviations from gross margin targets or enhancing value-based productivity) and to compete effectively within their respective local markets (e.g., against other

* Corresponding author.
E-mail addresses: idairaesthercbsz@hotmail.com (I. Cabrera-Suárez), josemaria.perez@ulpgc.es (J.M. Pérez-Sánchez).
[1] The views expressed here are those of the authors and not necessarily those of the institution with which they are affiliated.

https://doi.org/10.1016/j.iref.2026.104947
Received 15 November 2023; Received in revised form 11 October 2025; Accepted 20 January 2026
Available online 21 January 2026

banks or fintech firms).

Such heterogeneity affects the demand for banking services and shapes the optimal strategic approach for each branch. Consequently, significant productivity differences may emerge across branches due to variations in technological configurations. These differences are often influenced by heterogeneous environmental factors such as geographic location (e.g., urban vs. rural; industrial vs. service-based), customer base, internal organizational structure, and life-cycle stage. For example, Eskelinen et al. (2014) addressed this issue by segmenting bank branches operating in diverse environments into homogeneous groups based on overlapping specifications.

On the other hand, unobserved (latent) heterogeneity may also exist and differ among branches in terms of production (cost) efficiency. This may occur due to unobserved, non-systematic management problems that can be resolved by bank branches in the short term (Cabrera-Suárez & Pérez-Rodríguez, 2021), or systematic (persistent) management problems that can be addressed by decision-making units (DMUs) over the long term (Colombi et al., 2014; Filippini & Greene, 2016).[2]

Therefore, the production technology for bank branches can be heterogeneous because bank branches cannot share the same common production (or cost) function, which is to say the same vector of parameters in the production (cost). This approach assumes that the structure of the production function and the set of inputs and outputs are identical across all branches, although the relative importance assigned to each input and output may vary among them (e.g., due to the degree of specialization of each branch). For instance, while all branches operate with the same general categories of inputs and outputs, they may emphasize these differently depending on their client base or the predominant loan types (e.g., consumer vs. business loans), among other factors. The assumption of a common set of inputs and outputs is standard in most of the literature on stochastic frontiers and stochastic meta-frontiers (Jondrow et al., 1982; Battese et al., 2004), although some recent studies have explored alternative formulations (Cook et al., 2015; Li et al., 2016).

Ignoring technological heterogeneity can lead to either an overestimation or underestimation of inefficiency across branches, as well as to inconsistent parameter estimates when potential differences among branches are not accounted for in a panel data stochastic frontier model. Such misspecification may, in turn, distort branch rankings and hinder the accurate identification and evaluation of the most inefficient branches.

The empirical literature on bank branch efficiency has extensively used non-parametric methods to study technical or costs efficiency (see Paradi & Zhu, 2013; Cabrera-Suárez & Pérez-Rodríguez, 2020, for an overview), whereas the parametric approach based on stochastic frontier analyses has been less used. To our knowledge, only a few papers have analysed bank branch efficiency using stochastic frontier models. These include studies by Osiewalski and Marzec (1998) and Marzec and Osiewalski (2008, pp. 29–43), who assessed the cost efficiency of bank branches using a Bayesian framework, or, more recently, Cabrera-Suárez and Pérez-Rodríguez (2021), who studied unobserved heterogeneity and time-varying cost inefficiency of bank branches on a monthly basis.

Some studies in the literature have investigated technological gaps or group differences using the meta-frontier approach in a non-parametric framework (e.g., Goyal et al., 2019; Huang et al., 2022, for banks; and Noveiri and Kordrostami, 2022, for bank branches). However, no parametric models have been used to investigate the heterogeneity of technology in bank branches. One advantage of parametric models over non-parametric ones is that they allow for the explicit inclusion of the inefficiency term and the modelling of its determinants within a single-step procedure.

In this sense, the aim of this paper is to contribute to the literature on bank branch efficiency by proposing a model that accounts for technological heterogeneity across branches. Specifically, we address the following issues. First, we adopt a multi-input, multi-output production framework by specifying an output distance function modeled through a translog stochastic frontier approach, which provides a flexible representation of the underlying production technology. This framework enables us to account for the fact that bank branches operate with diverse resources and capabilities, which interact with the heterogeneity of local markets to shape their specialization strategies. To evaluate the effectiveness of these strategic choices, the output distance function captures the extent to which each branch approaches its optimal performance frontier, given its specific input configuration and operating environment.

Second, we employ a Bayesian random parameters model to explicitly incorporate technological heterogeneity among bank branches. The main advantage of this approach is that it can approximate "true" heterogeneous technologies and provide more accurate estimates of returns to scale (RTS) (Feng & Zhang, 2014). Furthermore, it allows us to disentangle unobserved technological heterogeneity from time-varying inefficiency in bank branches.

In this sense, our paper follows the methodology proposed by Feng and Zhang (2014) to model unobserved technological heterogeneity. However, unlike these authors, we model time-varying inefficiency by incorporating time-varying covariates—such as market size for assets (e.g., deposits) and liabilities (e.g., loans)—as well as a quadratic time trend. In addition, we compute the RTS for each bank branch to assess whether branches operate at the optimal scale (constant RTS) or exhibit decreasing or increasing RTS, and we also estimate productivity growth across branches.

The empirical analysis carried out to evaluate the performance of the branches and their managers was performed using yearly data (2011–2017) for the 122 branches of a large Spanish commercial bank.

The subsequent sections of this paper are organized as follows. In the next section, a concise overview of the literature regarding technological heterogeneity in banks will be provided. Section 3 describes a random parameter distance stochastic frontier model in a Bayesian framework. Section 4 displays both the data and the empirical results, leading to the presentation of the main conclusions in Section 5.

[2] For example, the error term in the panel data stochastic frontier model of Colombi et al. (2014) can be divided into four components that capture a firm's latent heterogeneity, persistent inefficiency, random shocks, and time-varying inefficiency.

2. Technological heterogeneity and efficiency

2.1. An overview on modelling heterogeneity in production

Tsekouras et al. (2017) argue that an incorrect treatment of technological heterogeneity distorts the benchmarking process and affects performance scores. They note that the effect of the technological structure on production due to heterogeneous behaviour and productive performance can be studied using different frontier methods, highlighting several approaches. These include the evaluation of heterogeneous behaviour in the context of unobserved heterogeneity with fixed and random effects (Colombi et al., 2014; Filippini & Greene, 2016), the latent class stochastic frontier approach for an appropriate treatment of unobserved differences in production technology (Orea & Kumbhakar, 2004), and the meta-frontier approach to calculate technology gaps between different levels of technology aggregation (Battese & Rao, 2002; Battese et al., 2004; or O'Donnell et al., 2006; among others). Tsekouras et al. (2017) introduced a new meta-frontier-based method to account for alternative technological hierarchies. They disentangled the layers of complexity triggering heterogeneous performance and introduced two types of heterogeneity, each referring to different stages of the performance evaluation process.

To the above list of methods can be added the random parameter approach, in which production (or cost) technology can be heterogeneous between DMUs by considering a random coefficient stochastic frontier model (e.g., Tsionas, 2002, or Greene, 2005; among others).

Tsekouras et al. (2017) also highlighted productive performance differentials considering different technological and economic structures. These differentials in a country frontier setting are due to country-specific mechanisms and market imperfections that result in efficient or inefficient resource allocation mainly through turbulence (Bartelsman et al., 2013; among others), and in a sector frontier setting to the asymmetric effects of emerging technologies on different industrial structures (Los & Verspagen, 2000, 2006; among others).

2.2. Technological heterogeneity in banks

Technological heterogeneity in the banking sector has generally been studied in two ways. Firstly, using the meta-frontier approach which allows consideration of the technological gaps between banks or branches. For example, Goyal et al. (2019) studied the efficiency levels of the overall Indian banking sector and across different ownership structures such as public, private and foreign banks. Huang et al. (2022) examined the cost efficiency, technology gap ratio, and overall cost efficiency of 43 banks and 27 life insurance companies operating in Taiwan. With respect to bank branches, Noveiri and Kordrostami (2022) recently proposed the use of a stochastic data envelopment analysis (DEA) approach to estimate the meta-frontier cost and revenue performance of heterogeneous bank branches under the convex technology.

However, technological heterogeneity in a banking context has predominantly been analysed using random parameters in a stochastic frontier framework because this enables the introduction of cross-firm heterogeneity by relaxing the restrictive hypothesis that technology is common across banks (Tsionas, 2002; Greene, 2005). In this regard, the few papers that have been published include a study by Tecles and Tabak (2010). In their analysis of bank efficiency in Brazil using a Bayesian stochastic frontier approach, large banks showed superior cost and profit effectiveness compared to certain public banks. They concluded that 'concentration favours efficiency'. In another study, this time employing a random parameter stochastic frontier cost function to analyse efficiency in 43 Mexican banks from 1998 to 2006, Barros and Williams (2013) found that this model produces more precise estimated efficiencies. A third example is the study conducted by Goddard et al. (2014), who used data from 1985 to 2010 from banks in four Latin American countries (Argentina, Brazil, Chile, and Mexico). They found that average efficiency estimates obtained with random parameter models tended to be higher than those found using fixed or random effects models. Moreover, the evolution of efficiencies varied over time with no similar pattern of behaviour between countries. They concluded that the type of bank ownership, regulation and context had a different impact in each country before, during and after the 2007 sub-prime crisis.

Feng and Zhang (2014) highlighted, in their literature review, evidence that unobserved technological heterogeneity is common among large banks in the US for several reasons. For example, the diffusion of new technologies among banks is not quick, because banks implement new technologies based on issues such as bank size, organizational structure, profitability, geographic location, and market structure (e.g., Akhavein et al., 2005; Saloner & Shepard, 1995). Furthermore, banks with different organizational structures use varying production technologies (e.g., Berger et al., 2005; Canales & Nanda, 2012; Coles et al., 2004), and banks with different business models often use alternative production technologies (e.g., Rossi, 1998).

Based on the above, Feng and Zhang (2014) modeled the RTS of large banks in the US in the presence of unobserved technological heterogeneity. To do so, they estimated a random parameters model based on the output distance frontier model along the lines of Tsionas (2002) and Greene (2005, 2008) to avoid a distorted ranking of banks and incorrect RTS estimation. Their results provided evidence of technological heterogeneity: most large U.S. banks exhibit constant RTS, banks of similar size display different RTS levels, and no clear pattern emerges among large banks regarding the relationship between asset size and RTS. More recently, Cortés-García and Pérez-Rodríguez (2024) studied the Ecuadorian banking sector using a Bayesian framework to estimate time-varying efficiencies and RTS in a translog output stochastic distance model, considering the technological heterogeneity of banks. Results indicated that randomness affected only the constant term, but not frontier parameters (e.g., input and technological change coefficients).

Regarding branches operating in heterogeneous environments, Eskelinen et al. (2014) addressed heterogeneity within a non-parametric efficiency framework by subdividing bank branches into homogeneous clusters based on overlapping specifications. Each cluster was then analysed separately to account for the heterogeneity among bank branches.

However, to our knowledge, no studies have been published that investigate unobserved technological heterogeneity in bank branches using a stochastic frontier analysis, allowing for differences in the production frontier due to heterogeneous environments or different groups (classes) of branches, among others.

3. Methodology

In this section, we define the random parameter models within a Bayesian framework, considering the output distance function and the translog specification.

3.1. A distance function stochastic production frontier model with random coefficients

The distance function with a translog production form allows measurement of the efficiency and productivity in different industries by analysing the relationship between multiple inputs and outputs in a flexible manner.

The general specification for this function is similar to that used in previous studies in the insurance and hotel industries. For example, the study by Eling and Luhnen (2010) used a similar distance function with a translog production form to examine the efficiency levels of various insurance companies. They included inputs such as labour, capital, and administrative expenses, and outputs such as premiums earned, and claims paid. Similarly, Assaf and Magnini (2012) and Assaf and Barros (2013) applied the distance function with a translog production form in the hotel industry to assess the efficiency of different hotels. They considered inputs such as labour, capital, and operating expenses, and outputs such as revenue and occupancy rates.

In addition to the inputs and outputs, our model also includes a quadratic trend to represent technological progress. This trend captures the impact of advancements in technology on efficiency and productivity over time.

The general representation of the translog output distance function for the scenario with M outputs and K inputs, within a fixed parameters framework (i.e., without the bank branch-specific heterogeneity), can be expressed as follows (O'Donnell & Coelli, 2005):

$$\log D_0(y,x,t) = \alpha + \sum_{m=1}^{M}\gamma_m \log y_m + \frac{1}{2}\sum_{m=1}^{M}\sum_{p=1}^{M}\gamma_{mp} \log y_m \log y_p + \sum_{k=1}^{K}\alpha_k \log x_k + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K}\alpha_{kj}\log x_k \log x_j + \sum_{k=1}^{K}\sum_{m=1}^{M}\delta_{km}\log x_k \log y_m$$
$$+ \kappa_1 t + \frac{1}{2}\kappa_2 t^2 + \sum_{m=1}^{M}\eta_m\, t \log y_m + \sum_{k=1}^{K}\theta_k t \log x_k. \qquad [1]$$

From Equation [1], Feng and Zhang (2014) derived an estimable form of the standard stochastic frontier model. In their approach, the coefficients were treated as fixed, i.e., identical across the entire sample. In contrast, in this paper we account for differences in the production frontier arising from heterogeneous environments or distinct branch groups by specifying a random-parameters model (Tsionas, 2002; among others).

The random parameters model allows for heterogeneous production technologies, which is evident when bank branches do not operate under a single efficient technology. Accordingly, all coefficients are permitted to vary across branches. It should be noted that, in our case, the random parameters model does not imply a different production function for each branch in terms of its structure; that is, the functional form of the production function (e.g., the translog output distance function) is identical for all branches. However, the parameter values may differ across branches, as assumed in our specification. Therefore, the translog output distance function with random parameters can be written as follows:

$$-\log y_{M,it} = \alpha_i + \sum_{m=1}^{M-1}\gamma_{m,i}\log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \frac{1}{2}\sum_{m=1}^{M-1}\sum_{p=1}^{M-1}\gamma_{mp,i}\log\left(\frac{y_{m,it}}{y_{M,it}}\right)\log\left(\frac{y_{p,it}}{y_{M,it}}\right) + \sum_{k=1}^{K}\alpha_{k,i}\log x_{k,it} + \frac{1}{2}\sum_{k=1}^{K}\sum_{j=1}^{K}\alpha_{kj,i}\log x_{k,it}\log x_{j,it} + \sum_{k=1}^{K}$$
$$\times\sum_{m=1}^{M-1}\delta_{km,i}\log x_{k,it}\log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \kappa_{1,i}t + \frac{1}{2}\kappa_{2,i}t^2 + \sum_{m=1}^{M-1}\eta_{m,i}\, t\log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \sum_{k=1}^{K}\theta_{k,i}t\log x_{k,it} + (v_{it}+u_{it}), \qquad [2]$$

where log represents the natural logarithm, $i = 1, 2, ..., n$ is the number of bank branches, $t = 1, 2, ..., T_i$ is the number of time periods, $m, p = 1, \ldots, M-1$ is the number of outputs, $k, j = 1, \ldots, K$ is the number of inputs, $y_{m,it}$ is the output m of bank branch i in period t; and α_i, $\gamma_{m,i}$, $\gamma_{mp,i}$, $\alpha_{k,i}, \alpha_{kj,i}, \delta_{km,i}, \kappa_{1,i}, \kappa_{2,i}, \eta_{m,i}$, and $\theta_{k,i}$ are unknown parameters. It is noteworthy that the behaviour of these parameters is random, as they depend on a random error term. As an example, the parameter $\gamma_{m,i}$ in Equation [2] can be decomposed into its mean and a random vector which captures the bank branch-specific heterogeneity:

$$\gamma_{m,i} = \overline{\gamma}_m + \epsilon_i, \qquad [3]$$

where the vector of random parameters ϵ follows a multivariate normal distribution with a mean vector of zeros and covariance matrix Σ ($\epsilon \sim N(\overline{0}, \Sigma)$). The standard fixed parameters model of Feng and Zhang (2014) is recovered by setting $\epsilon = 0$.

The error terms capture the statistical noise $v_{it} \sim N(0, \sigma_v^2)$ and the inefficiency $u_{it} \sim Exp(\lambda_{it})$, with Exp denoting an exponential distribution with parameter $\lambda_{it} = Exp(\beta' z_{it})$ depending on the vector of environmental variables z_{it}. It should be noted that the expected inefficiency in this study is computed as $E[u_{it}] = 1/\lambda_{it} = \frac{1}{Exp(\beta' z_{it})}$.

From the translog function, it is possible to obtain other measures of interest. Thus, from Equation [1] it is straightforward to obtain the elasticity of the output distance function with respect to each input, x_k, defined as:

$$\varepsilon_{k,it} = \frac{\partial log\ D_0(y,x,t)}{\partial log\ x_{k,it}} = \alpha_{k,i} + \sum_{j=1}^{K} \alpha_{kj} log\ x_{j,it} + \sum_{m=1}^{M} \delta_{km,i}\ log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \theta_{k,i} t, \quad [4]$$

and the output-distance-function-based measure of RTS, defined as (Caves et al., 1982; Orea, 2002):

$$RTS_{it} = -\sum_{k=1}^{K} \varepsilon_{k,it}. \quad [5]$$

In addition to RTS, we can also estimate two related measures: technical change (TC) and efficiency change (EC). These can be calculated, respectively, as the differences in the distance frontier and in efficiency between periods *t* and *t-1* (Assaf et al., 2013):

$$TC_{it} = \sum_{m=1}^{M-1} \eta_{m,i}\ log\left(\frac{y_{m,it}}{y_{M,it}}\right) + \sum_{k=1}^{K} \theta_{k,i} log\ x_{k,it} + \kappa_{1,i} + \frac{1}{2}\kappa_{2,i}\left(t^2 - (t-1)^2\right) + \left(u_{it} - u_{i(t-1)}\right). \quad [6]$$

$$EC_{it} = \exp(-u_{it}) - \exp(-u_{i(t-1)}). \quad [7]$$

Finally, we obtain the productivity change by taking the sum of TC and EC.

3.2. Bayesian procedure

In this subsection, we specify the Bayesian estimation of the translog stochastic distance frontier for two models: the standard fixed parameters model, which has been widely used in the stochastic frontier literature (Koop & Steel, 2003; O'Donnell & Coelli, 2005; for example), and the random parameters model, which considers individual-specific unobserved heterogeneity across all inputs (Tsionas, 2002; Feng & Zhang, 2014).

For both models, and to facilitate comparisons and ensure robustness, we specify identical priors for the parameters that are shared across models. The priors employed in the Bayesian model are non-informative, as we assume an objective Bayesian approach. A Normal distribution with mean 0 and variance sufficiently large to express disinformation is usually assumed for the coefficients of the model. However, a small variation is needed to ensure that the conditions of monotonicity are satisfied. These conditions require that $\frac{\partial log\ D_0(y,x,t)}{\partial log\ x_k} \le 0$ and $\frac{\partial log\ D_0(y,x,t)}{\partial log\left(\frac{y_{m,it}}{y_{M,it}}\right)} \ge 0$ in Equation [2]. For the random parameters model, the expression of these derivatives are given in [4] and:

$$\frac{\partial log\ D_0(y,x,t)}{\partial log\left(\frac{y_{m,it}}{y_{M,it}}\right)} = \gamma_{m,i} + \sum_{p=1}^{M-1} \gamma_{mp,i}\ log\left(\frac{y_{p,it}}{y_{M,it}}\right) + \sum_{k=1}^{K} \delta_{km,i} log\ x_{k,it} + \eta_{m,i} t. \quad [9]$$

To simplify these nonlinear constraints and following O'Donnell and Coelli (2005) and Feng and Zhang (2014), we deflate the sample data so that all output and input variables have a sample mean of one, and the-time trend has a sample mean of zero. Therefore, the monotonicity conditions at the mean can be expressed as $\alpha_{k,i} \le 0$ and $\gamma_{m,i} \ge 0$ for $k = 1, \ldots, K$ and $m = 1, \ldots, M$. To guarantee compliance with these conditions, we specify flat gamma prior distributions for these parameters. In summary:

- α_i, γ_{mp}, $\alpha_{kj,i}, \delta_{km,i}, \kappa_{1,i}, \kappa_2, i, \eta_{m,i}, \theta_{k,i} \sim N\left(0, 10^6\right)$ (as in Tsionas, 2002; Feng & Zhang, 2014).
- $\gamma_{m,i}, -\alpha_{k,i} \sim$ G $(0.01, 0.01)$ (as in Lambert et al., 2005).

In Equation [2], the compound error $(v_{it} + u_{it})$ is asymmetric, where v_{it} is assumed to be i.i.d. $N\left(0,\sigma_v^2\right)$, with $1/\ \sigma_v^2 \sim$ G$(0.01, 0.01)$, and u_{it} is a non-negative component and one-sided component error (inefficiency term), which is assumed to be an i.i.d. random variable defined by the exponential distribution (as, for example, in Koop et al., 1997) with parameter $\lambda_{it} = Exp(\beta' z_{it})$, where λ_{it} depends on the vector of environmental variables, z'_{it}, and the vector of unknown parameters, β. The β parameters also follow a prior Normal distribution with mean 0 and variance 10^6.

The random parameters model includes bank branch-specific parameters. Each parameter can be decomposed into its mean and a random vector with zero mean which captures the bank branch-specific heterogeneity. We assume the same prior distributions for the means as assumed in the standard fixed parameters model. The random vector ϵ follows a multivariate normal distribution with a vector of zeros as mean and covariance matrix $\sum$. A prior inverse Wishart density is assumed for the variance matrix $\sum$, with $r = 1$ degrees of freedom and scale matrix $\Omega = 10^{-6} \cdot I$, where I denotes the identity matrix ($\sum \sim IW(r, \Omega)$) (Tsionas, 2002).

4. Empirical analysis

4.1. Data

In this study, two sources of bank branch data were used for a Spanish commercial bank. Profit and loss statements were used to compile the annual accounting information for the period 2011–2017 (seven years), along with supplementary information from internal departments (e.g., management control and human resources, among others). These branches are widely distributed across Spain and provide the same types of service, handling both personal and business accounts. They include small and large branches and are located in rural and urban areas (including street branches, shopping centers, among others), some of which have a high concentration of branches. For reasons of confidentiality, no further identification is provided.

The original sample size of branches to be studied was 151 and the sample was not winsorized. However, 29 branches presented some problems. For example, some branches presented extreme values for certain input and output variables due to accounting adjustments. Some others were closed or merged with other nearby branches during the study period. These circumstances could have influenced the estimation procedure and, to prevent distortion from these sources, the branches in question were therefore eliminated from the sample. After filtering the database in this way, a total of 122 out of 151 bank branches remained for analysis. It should also be noted that part of this data period (2011–2014) was previously employed by Cabrera-Suárez and Pérez-Rodríguez (2020, 2021) to evaluate the effectiveness of branch operations and managerial conduct in a large Spanish commercial bank. The panel is balanced, with a total number of observations equal to 854.

The literature on banking efficiency has traditionally distinguished between two theoretical frameworks for modeling the production function of financial institutions: the production approach and the intermediation approach (Berger & Humphrey, 1997). In this study, we adopt the production approach, which conceptualizes the branch as an operating unit whose primary function is the provision of transactional services to customers. From this perspective, and in line with Paradi and Zhu (2013), branches transform inputs—such as labor (e.g., number of employees) and physical capital (e.g., fixed assets or office space)—into outputs reflecting their activity, such as the number of deposit transactions, the volume of transactions processed, or newly opened accounts.

The adoption of the production approach is methodologically appropriate for this study, as the objective is to assess operational efficiency at the branch level, rather than the efficiency of managing the institution's overall financial balance sheet.

Below, we describe the outputs, inputs and environmental variables used in our analysis (see Table A1 in the Appendix for their definitions and sources of data) at the bank branch level. In general, these variables are common in many DEA studies on banks (see Camanho & Dyson, 1999, 2006; Paradi & Zhu, 2013, among others).

4.1.1. Outputs

The outputs used in this study have also been employed by other authors, such as Camanho and Dyson (1999, 2006) and Giokas (2008). Specifically, we consider the value of savings (savings deposit accounts) and the value of loans—including mortgages for both consumer and business accounts—at the branch level. It is important to note that our analysis does not incorporate account activity (calculated by the total number of transactions) due to data only being available from 2013.

4.1.2. Inputs

To specify the model, a set of input variables is defined to represent the discretionary resources that branch management employs in the production process. These primarily include labor (e.g., number of employees) and physical capital (e.g., fixed assets).

Following Camanho and Dyson (1999, 2006) and Cabrera-Suárez and Pérez-Rodríguez (2020), we use the following branch-level inputs: the total number of full-time equivalent employees (including branch and account managers, administrative and commercial staff, and tellers, who account for the majority of branch costs); the floor space utilized by each branch (measured in m^2); the number of external ATMs associated with each branch; and the operational costs incurred (including the total costs of materials, space, and information systems, but excluding personnel costs).

It should be noted that, in line with common practices in the Spanish banking sector, the bank operates a network of ATMs located outside its branches, referred to as “displaced ATMs.” These are situated in strategic, high-traffic locations—such as shopping malls, airports, and large business centers—with the aim of maximizing network coverage and customer accessibility. Over the past decade, however, there has been a general trend toward reducing the ATM fleet. This structural adjustment is primarily driven by two sector-specific factors: (a) the accelerated digitalization of financial services, which has decreased dependence on cash and reduced the demand for transactions at physical terminals, and (b) bank consolidation processes, which have promoted the optimization and rationalization of service networks to eliminate redundancies and lower operating costs. Such strategies are part of ongoing cost-optimization processes conducted during annual reviews.

4.1.3. Environmental variables

Furthermore, a vector of environmental variables is incorporated to obtain robust estimates in the stochastic frontier analysis, as branches are exposed to exogenous, non-discretionary factors that define their operating environment. These factors—such as competitive pressure, local macroeconomic conditions, or demographic characteristics—are beyond the branch's control but can influence its ability to transform inputs into outputs. Their inclusion is therefore necessary to avoid bias in the efficiency scores.

Due to data availability, we include only a few environmental variables to explain efficiency. Specifically, we consider the market share of loans and deposits (Tecles & Tabak, 2010), which serve as proxies for branch size in terms of assets and liabilities, respectively. Previous studies, such as Williams (2004), also used market-share indicators to account for organizational structures in savings banks when explaining cost inefficiency. Larger market sizes can enable branches to achieve economies of scale, potentially lowering average costs per unit of output and improving efficiency. In this study, we calculate the market share of loans as branch loans divided by total institutional loans in a given year, yielding a value between 0 and 1 that indicates the relative prominence of the branch in lending. Similarly, market share of deposits is computed as branch savings divided by total institutional savings.

In addition, we include linear and quadratic time trends in the frontier and efficiency models to capture technical change.

Table 1 shows descriptive statistics for the outputs, inputs and environmental variables used in the efficiency model. All data values are reported in constant 2011 euro, calculated using the consumer price index of the local market with respect to the base period 2011.

The most notable feature revealed by the table is the extreme heterogeneity of the sample, which provides the primary empirical justification for the use of a random parameters model.

- **Outputs**: Both product variables (deposits and loans) exhibit a strong right skew. This is evident when comparing the mean with the median (e.g., for loans, €33.6 million vs. €26.0 million), indicating that the sample includes a small number of branches with substantially higher turnover than the typical branch.
- **Inputs**: Heterogeneity is even more pronounced in the inputs.
  - o The number of employees and operating costs also show a clear positive skewness.
  - o The most notable variable is branch area. The standard deviation (306 m^2) is nearly as large as the mean (343 m^2), resulting in a coefficient of variation (CV = SD/Mean) of approximately 0.89. A CV so close to 1 indicates substantial dispersion. Branch sizes range from very small (90 m^2), typically in rural areas, to exceptionally large (1,594 m^2), usually in urban areas with high traffic and commercial activity. This provides compelling evidence that branches operate at different scales and possibly under different production technologies.
- **Environmental variables**: The distribution of market shares is also skewed, with maximum values (5.51 % and 3.18 %) several times higher than the mean (0.82 %). This confirms that some branches are strategically far more important to the bank than the majority.

The mean total value of deposits per branch is approximately €11 million, while the mean total value of loans reaches €34 million. On average, each branch operates 3 ATMs and employs 4 staff members. It is noteworthy that the minimum number of employees is 1, corresponding to a branch located in an area of low commercial activity. Such branches are often maintained due to historical agreements or traditional locations, reflecting the bank's interest in preserving these sites.

Current trends in the financial sector, however, favour the establishment of larger branches in urban or metropolitan centers, enabling them to serve a broader segment of clients and host specialized sales forces, for example in Small and Medium Enterprises (SMEs). To compensate for areas without physical branches, banks are increasingly developing more digital services to reach underserved locations.

The average branch size is approximately 343 m^2, with an average market share of 0.82 % for both deposits and loans, and average operational costs of €154,000 per branch. During the period analysed, there was a general trend toward a reduction in the number of employees and ATMs, as well as the closure of some branches. These descriptive statistics reflect a snapshot of a period of restructuring for the institution.

The coexistence of branches with only one employee alongside others with more than ten, as well as the variation in physical size, illustrates a diversified branch portfolio that was being optimized during the years studied. Between 2011 and 2017, the Spanish banking sector underwent profound restructuring, marked by the aftermath of the financial crisis, the 2012 European bank bailout, and regulatory mandates to improve efficiency. This period saw intense sector consolidation and an unprecedented adjustment in capacity, with the branch network shrinking by over 30 % from its peak.

Consequently, the high heterogeneity observed in the sample—evident in the coefficient of variation in branch size and employee numbers—reflects not only statistical variation but also a commercial network in full transformation. Some branches were in the process of closure, others were merging with nearby units, and larger branches served as consolidation centers within the new post-

Table 1
Descriptive statistics for bank branches over the period 2011–2017.

Variable	Mean	Standard deviation	Min.	25th percentile	Median	75th percentile	Max.
Outputs							
y_1: Value of deposits (million euros)	10.9	1.09	0.71	4.27	6.5	13.7	72.1
y_2: Value of loans (million euros)	33.6	23.7	4.2	17.0	26.0	44.0	140.0
Inputs							
x_1: Number of ATMs	2.9344	1.3782	1	2	3	4	8
x_2: Number of full employees	3.7695	2.4975	1	2	3	4	13
x_3: Operational costs (€)	154,221.63	89,076.76	9,887.12	94,106.08	127,255.50	183,328.78	561,597
x_4: Floor space of the branch (in m^2)	343.4344	306.3668	90	175	225	350	1,594
Environmental variables							
z_1: Market share of deposits	0.0082	0.0082	0.0006	0.0032	0.0050	0.103	0.551
z_2: Market share of loans	0.0082	0.0058	0.0011	0.0042	0.0063	0.109	0.318

Notes: This table presents the descriptive statistics for the pooled sample over the period 2011–2017. The statistics reported include the mean, standard deviation, minimum, 25th percentile, median, 75th percentile, and maximum.

crisis commercial structure.

4.2. Time-varying efficiency

Bayesian estimation results were obtained using the *OpenBUGS* program. The Markov chain Monte Carlo (MCMC) algorithm ran for 200,000 iterations, with the first 100,000 discarded during the 'burn-in' phase. The MCMC simulation for the random parameters model was performed with a thinning interval of 5 to ensure convergence. Chain stability was assessed using the Geweke (1992) convergence test which compares the initial and final 20 % of the MCMC simulation. Test results and graphs were obtained with the STATA 17 software package.

Table 2 shows the Bayesian results for the translog stochastic distance production frontier defined by Equation [2]. Table 2 (Panel A) shows the posterior mean, statistical relevance, MC error, and the probability associated with Geweke's convergence test for the coefficients of the fixed and random parameters models. Both models consider the inclusion of several covariates in the (in)efficiency model (Panel B), such as the market share of deposits and loans in the local market and a quadratic trend representing the change over time. Note that input and output parameter estimates were restricted to maintain monotonicity conditions valid for our distance production function, namely positive values for output coefficients and negative values for input coefficients (see Feng & Zhang, 2014, and references therein).

Focusing on Table 2 (Panel A), several parameter coefficients are statistically significant considering the centered credible interval in both models. Although the estimates vary, certain similarities can be observed regarding the sign and statistical relevance of the coefficients in both models. All the coefficients pass the Geweke convergence test at a 5 % significance level. It is noteworthy that, when comparing the two models, the deviance information criterion (DIC) indicates that a random parameters model is preferable to the fixed parameters model. This result supports the relevance of incorporating unobserved technological heterogeneity for the bank branches.

Regarding the determinants for expected inefficiency ($1/\lambda_{it}$) (Table 2, Panel B), the coefficients for market share of deposits and loans are positive. In our model, this implies that as the market share for deposits and loans increases, expected inefficiency decreases, indicating a corresponding increase in efficiency. This result is in line with some papers in the empirical literature on bank branches (e.g., Cabrera-Suárez & Pérez-Rodríguez, 2021). Furthermore, the fixed parameters model does not detect variations in efficiency over time, whereas the random parameters model does detect a non-linear increase.

To illustrate the behaviour of overall efficiency estimates and their temporal patterns, Fig. 1 presents the posterior expected technical efficiency distribution, along with the year-by-year evolution of the empirical distributions for both models. More specifically, Fig. 1a shows the kernel density estimates for the overall efficiencies, which are high, in general, in both models, and mostly concentrated over 0.95. The DIC statistic indicates that the random parameters model is statistically preferable. Therefore, we can examine the consequences of failure to allow for technological heterogeneity between branches. As Fig. 1a shows, higher efficiencies are observed in the random parameters model, suggesting that the random parameters model allows for a more accurate adjustment of the frontier for each branch. Thus, for example, the proportion of efficiencies above 95 % estimated by the fixed parameters model is 45.08 %, compared to 67.33 % in the random parameters model. However, Fig. 1a also shows, as expected, that efficiencies are skewed to the left with a slightly longer tail for the random parameters model. Estimating a particular frontier for each bank branch allows for a better appreciation of the more efficient and more inefficient periods of the branches, whereas the joint analysis with a unique production function cannot capture these extremes. It is noteworthy that the maximum observed difference between the average annual efficiencies estimated by the two models occurred in 2017, reaching 0.0752.

Fig. 1b shows the efficiencies by year. The differences are markedly present at the end of the sample (2016–2017, when the International Financial Reporting Standard (IFRS) was revised).[3] There is a clear increase in technical efficiency compared to the previous years in the random parameters model which is not observed in the fixed parameters model.

Table 3 shows the descriptive statistics for posterior expected technical efficiency obtained from the fixed and random parameters models. Mean efficiency varies only slightly over the study period in the fixed parameters model, with the lowest technical efficiency recorded at 0.8646 in 2011. The highest efficiency is observed in the random parameters model, reaching 0.9801 in 2017.

Although the estimated efficiencies vary between models, the ranking of branches by efficiency is not drastically altered. The Spearman correlation between both efficiencies is above 0.95 for the period 2011–2016, with 2017 being the only year with a slightly lower Spearman correlation (0.8815).

4.3. Returns to scale

The production technology for each bank branch can exhibit increasing, constant and decreasing RTS, expressing the correlation, or lack thereof, between variations in output after altering all inputs in equal measure.

Fig. 2 shows the RTS for both models considering the kernel density estimates (Fig. 2a) and the RTS by year (Fig. 2b). Two notable observations regarding bank branches emerge from these figures.

First, Fig. 2a highlights marked differences between the two models due to the presence of technological heterogeneity. Although the mean RTS over time is similar for both models (1.07 for the fixed parameters model and 1.12 for the random parameters model),

[3] Under International Financial Reporting Standard 9 (IFRS9) (see International Accounting Standards Board (2014a, b)), the role of provisions is to cover for anticipated losses in the future. Since 2018, European banks have followed the IFRS9 approach.

Table 2
Panel data estimates with covariates of mean inefficiency for the translog input stochastic distance frontier model. Fixed and random parameters models.

Variable	Fixed parameters model			Random parameters model					
	Coefficient	MC error	Geweke	Coefficient mean	MC error	Geweke	Standard deviation	MC error	Geweke
Panel A: Translog stochastic distance production function									
Intercept	−0.0049	0.0003	−0.3554	0.0223	0.0006	0.0439	0.0651**	0.0001	0.9028
log y_1/y_2	0.2997**	0.0002	0.4393	0.2377**	0.0004	−0.1185	0.0734**	0.0001	0.4604
$(\log y_1/y_2)^2$	−0.0527	0.0004	0.0803	−0.0391	0.0009	−0.0228	0.0397**	0.00007	0.0677
log x_1	−0.1673**	0.0006	0.2868	−0.2383**	0.0008	−0.4006	0.0231**	0.00009	1.0452
log x_2	−0.6222**	0.0005	0.5027	−0.5620**	0.0006	0.1174	0.0104**	0.00006	1.0342
log x_3	−0.2918**	0.0005	0.1029	−0.2997**	0.0007	0.1582	0.0156**	0.00007	0.3575
log x_4	−0.0043**	0.0006	−0.7913	−0.0082	0.0007	−0.0991	0.0015**	0.00005	0.6837
$(\log x_1) \times (\log x_2)$	0.1801*	0.0019	−0.1866	0.2227**	0.0035	0.1174	0.0047**	0.00005	1.4113
$(\log x_1) \times (\log x_3)$	0.0715	0.0035	0.1418	−0.0298	0.0051	0.1593	0.0232**	0.00008	0.2453
$(\log x_1) \times (\log x_4)$	−0.1107	0.0013	0.5117	−0.1980**	0.0027	−0.2304	0.0379**	0.00007	−0.4826
$(\log x_2) \times (\log x_3)$	−0.1334	0.0031	0.1315	−0.0962	0.0041	−0.0718	0.0489**	0.00009	0.3579
$(\log x_2) \times (\log x_4)$	0.0029	0.0011	−0.3065	0.0176	0.0017	−0.1716	0.0188**	0.00004	0.6927
$(\log x_3) \times (\log x_4)$	0.2185**	0.0011	−0.1765	0.2979**	0.0022	0.2208	0.0623**	0.0001	0.5007
$(\log x_1) \times (\log x_1)$	−0.2281	0.0041	−0.3163	0.1526	0.0067	0.0819	0.0196**	0.00007	0.3345
$(\log x_2) \times (\log x_2)$	0.0024	0.0030	0.1613	−0.1034**	0.0046	0.0230	0.0334**	0.0001	−0.7205
$(\log x_3) \times (\log x_3)$	−0.0187	0.0032	−0.3147	−0.0258	0.0041	0.0230	0.0153**	0.00005	0.8600
$(\log x_4) \times (\log x_4)$	−0.2243**	0.0009	0.5916	−0.2970**	0.0018	0.0979	0.0652**	0.0001	0.5582
$(\log x_1) \times (\log y_1/y_2)$	0.0802	0.0011	−0.2127	0.0875	0.0018	0.1595	0.0157**	0.00007	0.3748
$(\log x_2) \times (\log y_1/y_2)$	0.0014	0.0009	0.0774	0.0061	0.0013	0.1256	0.0018**	0.00003	0.9603
$(\log x_3) \times (\log y_1/y_2)$	−0.2170**	0.0012	0.3129	−0.2372**	0.0015	0.0582	0.0164**	0.00007	−0.7821
$(\log x_4) \times (\log y_1/y_2)$	0.1328**	0.0005	−0.2052	0.0909*	0.0013	−0.2094	0.0985**	0.0001	0.2603
t	0.0221**	0.00006	−0.2324	0.0207**	0.0001	−0.1925	0.0279**	0.0001	−0.3960
t^2	0.0062	0.00006	0.6218	0.0152**	0.00009	0.1205	0.0286**	0.00006	0.0721
$t \times (\log y_1/y_2)$	−0.0076	0.00007	−0.1801	−0.0165*	0.0001	0.2010	0.0377**	0.00009	−0.0385
$t \times (\log x_1)$	−0.0036	0.0001	0.0186	−0.0298*	0.0003	0.1857	0.0542**	0.00009	0.0690
$t \times (\log x_2)$	0.0384**	0.0001	0.0485	0.0498**	0.0003	−0.0380	0.0194**	0.0001	−0.4390
$t \times (\log x_3)$	−0.0327**	0.0002	−0.0637	−0.0463**	0.0004	0.0739	0.0118**	0.00006	−0.2884
$t \times (\log x_4)$	−0.0117	0.00006	0.2015	−0.0095	0.0001	−0.0719	0.0152**	0.00006	−0.3633
Panel B: Efficiency									
Intercept	3.690**	0.0090	0.4402	3.856**	0.0131	−0.1344			
log z_1	1.665**	0.0036	0.5162	1.781**	0.0055	−0.0133			
log z_2	0.7802**	0.0050	0.1609	0.6139**	0.0081	−0.3181			
t	0.0257	0.0006	−0.1915	0.1898**	0.0018	−0.1451			
t^2	0.0041	0.0003	0.7946	0.1217**	0.0009	0.3067			
DIC	−372.4			−945.1					
Bank branches	122			122					
Observations	854			854					

Notes: DIC = deviance information criterion; ** 95 % centered credible interval (CCI) does not contain 0; * 90 % CCI does not contain 0.

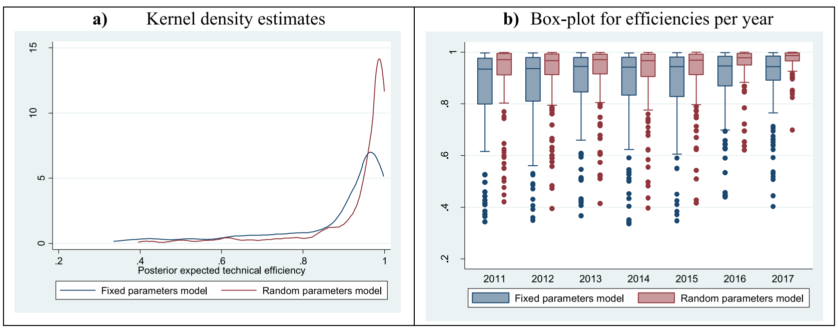

Fig. 1. Posterior expected technical efficiencies and time-path distribution of technical efficiencies per year for fixed and random parameter models. ***Note:*** This figure shows two graphs which allows identification of the distribution of efficiencies and the patterns of efficiencies over time estimated using the translog input stochastic distance frontier, considering the fixed and random parameters models and employing a Bayesian framework. To do so, we plotted the kernel density estimates for efficiencies and the time-varying boxplots of efficiencies for both models.

Table 3
Descriptive statistics for posterior expected technical efficiency.

TE	Fixed parameters model					Random parameters model				
	Mean	Median	SD	$Z_{2.5\ \%}$	$Z_{97.5\ \%}$	Mean	Median	SD	$Z_{2.5\ \%}$	$Z_{97.5\ \%}$
2012	0.8646	0.8647	0.01328	0.8382	0.8904	0.9174	0.9175	0.01385	0.8896	0.9445
2013	0.8742	0.8744	0.01107	0.8523	0.8956	0.9080	0.9082	0.01041	0.8873	0.9281
2014	0.8883	0.8885	0.00982	0.8685	0.9071	0.9129	0.9131	0.00853	0.8958	0.9293
2015	0.8810	0.8813	0.01059	0.8596	0.9012	0.9021	0.9022	0.00987	0.8826	0.9212
2016	0.8836	0.8838	0.01053	0.8623	0.9036	0.9209	0.9210	0.00935	0.9022	0.9390
2017	0.9009	0.9011	0.00986	0.8809	0.9195	0.9583	0.9587	0.00755	0.9425	0.9721

Notes: TE: Technical efficiency. SD: Standard deviation. $Z_{2.5}$ %: Posterior 2.5 % percentile. $Z_{97.5}$ %: Posterior 97.5 % percentile.

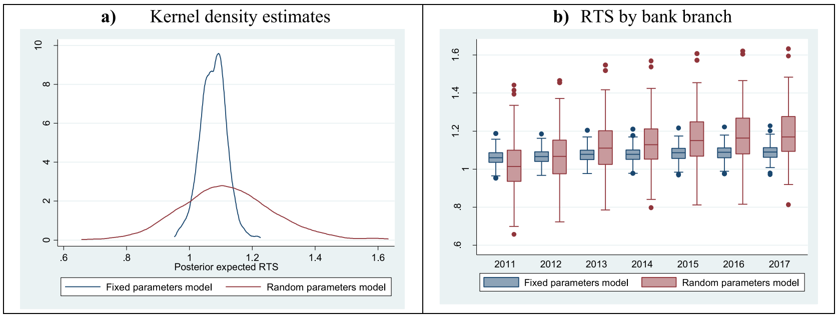

Fig. 2. Posterior expected returns to scale (RTS) for the study period (2011–2017).
Note: This figure shows two graphs which allow identification of the distribution of returns to scale (RTS) and the patterns of RTS over time estimated using the translog input stochastic distance frontier, considering the fixed and random parameters models and employing a Bayesian framework. To do so, we plotted the kernel density estimates for efficiencies and the time-varying boxplots of RTS for both models.

dispersion is greater in the random parameters model. Ignoring technological heterogeneity when modelling bank branch efficiency could therefore lead to misleading conclusions, including underestimation of RTS dispersion. A similar finding regarding higher dispersion in random parameters models was reported by Feng and Zhang (2014) for large banks in the USA.

Second, Fig. 2b shows that this dispersion persists over time in the random parameters model and reveals a more pronounced trend than in the fixed parameters model. This temporal pattern suggests that branch rankings could differ significantly if technological heterogeneity is ignored, particularly regarding increasing (RTS>1), constant (RTS = 1), and decreasing (RTS<1) returns to scale.

To analyse this issue, we calculate the percentage of bank branches exhibiting increasing, constant and decreasing RTS, for both the fixed and random parameters models. Following Feng and Zhang (2014), these percentages are calculated by counting the number of

Table 4
Percentage of bank branches with increasing, constant and decreasing returns to scale (RTS).

Year	*n*	*Increasing RTS (%)*	*Constant RTS (%)*	*Decreasing RTS (%)*
***Panel A**: Fixed parameters model*				
2011	122	8.20	91.80	0
2012	122	15.57	84.43	0
2013	122	30.33	69.67	0
2014	122	31.97	68.03	0
2015	122	36.06	63.94	0
2016	122	31.97	68.03	0
2017	122	27.05	72.95	0
Average		25.88	74.12	0
***Panel B**: Random parameters model*				
2011	122	23.77	60.66	15.57
2012	122	37.70	52.46	9.84
2013	122	52.56	43.44	4.10
2014	122	55.74	42.62	1.64
2015	122	59.02	40.16	0.82
2016	122	59.84	40.16	0
2017	122	59.84	40.16	0
Average		49.77	45.67	4.56

Notes: This table presents the returns to scale (RTS) estimated from the translog input stochastic distance frontier, using both the fixed- and random-parameters models within a Bayesian framework. The table reports the percentage of branches exhibiting increasing, constant, and decreasing RTS, respectively. The variable *n* denotes the number of branches each year.

cases where the 95 % credibility interval is strictly above 1 (increasing RTS), includes one (constant RTS), and is strictly lower than one (decreasing RTS).

Table 4 presents these results. According to the fixed parameters model (Panel A), the branch network appears to operate largely at an optimal scale.

- Dominance of Constant RTS: On average, 74 % of branches exhibit constant returns to scale, suggesting that they have reached their optimal size.
- Absence of Excessive Scale Inefficiency: Notably, this model does not identify any branch with decreasing returns to scale (0 %) over the entire period.

In summary, relying on the fixed parameters model would lead managers to conclude that the branch network is well-sized, with limited opportunities for efficiency improvements through adjustments in scale.

The random-parameters model (Panel B), which is statistically superior according to our study, presents a markedly different and more complex picture.

- Dominance of Increasing RTS: This model indicates that a majority—and an increasing proportion—of branches operate with increasing returns to scale, reaching nearly 60 % from 2015 onward. Specifically, the percentage of branches with increasing RTS rises from 23.77 % in 2011 to 59.84 % in 2016 and 2017, suggesting substantial potential for efficiency gains if these branches expand their size and business volume.
- Detection of Scale Inefficiency: In contrast to the fixed-parameters model, the random-parameters approach identifies a share of branches experiencing decreasing returns to scale (e.g., 15.6 % in 2011), which the fixed model completely masked.

Given that failed branches were excluded from the analysis, the predominance of increasing RTS provides an insightful perspective on banking consolidation. Branches exhibiting increasing RTS indicate that the average production cost decreases as output (e.g., loans, deposits) expands, highlighting the potential for branch consolidation. The divergence between the two models leads to contrasting strategic implications: the fixed-parameters model suggests an optimal status quo, whereas the random-parameters model reveals a network with substantial opportunities for improvement. Most branches appear undersized and could benefit from expansion, while a minority—particularly at the beginning of the period—operate at inefficiently large scales.

This finding underscores that ignoring technological heterogeneity is not merely an econometric oversight but may also result in misguided management and policy decisions. Notably, the subsequent evolution of the bank's commercial network aligns with the predictions of the random parameters model. The bank's de facto consolidation strategy—closing smaller branches in low-density or geographically redundant locations and reinforcing branches with increasing returns to scale—reflects the resource optimization suggested by the model's results. This ex-post evidence provides additional robustness to the study's main conclusions.

In addition, these results show that unobserved technological heterogeneity in inputs could be useful in identifying the branches that do not operate at the optimal size level and, subsequently, in defining specific bank branch policies to address this situation.

4.4. Productivity growth

In this subsection, we present the results of estimated productivity growth for the bank branches, along with its decomposition into technical and efficiency changes, following the expressions proposed by Feng and Zhang (2014, p. 143).

Table 5 shows the results for the fixed and the random parameters models. More specifically, the table shows productivity growth and its decomposition between technical change and efficiency change.[4] Comparing the fixed and random parameters model estimates, we can see significant differences in the estimated magnitudes, although the signs of the magnitudes that are statistically relevant coincide. Focusing on the random parameter estimates, productivity growth oscillates around zero, with an annual increase of 3.917 % in 2016, and a decrease of 4.145 % in 2014. As observed, the contribution of efficiency changes to productivity growth is consistently positive and exceeds that of technical change. This effect exhibits considerable temporal stability, with an increase in efficiency in 2013, a slight decline in 2014, followed by a sustained upward trend, reaching the highest annual growth rate of 3.756 % in 2016.

The finding that efficiency change was the primary driver of productivity growth, while technical change was often zero or negative, provides important insight into the entity's corporate strategy during the study period. This result goes beyond a mere metric, reflecting a fundamental strategic decision.

These findings suggest that management prioritized intensive operational rationalization rather than an expansive innovation strategy—that is, they focused on optimizing existing resources and processes rather than developing or adopting new technologies to shift the production frontier. In practice, this strategy involved:

- Dissemination of Best Practices: Processes from the most efficient branches were identified and replicated across the network through internal benchmarking. For example, sales managers with the highest performance ratios were analysed to understand

[4] Table A2 shows the data envelopment analysis using Malmquist indices. Comparing both Malmquist and random parameter model estimates, significant differences in the estimated magnitudes can be seen.

Table 5
Productivity growth.

Period	Fixed parameters model			Random parameters model		
	Average annual productivity growth (%)	Technical change (% contribution)	Efficiency change (% contribution)	Average annual productivity growth (%)	Technical change (% contribution)	Efficiency change (% contribution)
2011–2012	1.516 [-2.666, 5.751]	0.554 [-2.248, 3.372]	0.962 [-0.946, 2.913]	−0.969 [-4.355, 2.404]	−0.043 [-2.527, 2.446]	−0.615 [-1.646, 0.683]
2012–2013	1.784 [-2.158, 5.761]	0.376 [-2.121, 2.861]	1.408 [-0.333, 3.171]	0.671 [-2.466, 3.810]	0.183 [-1.863, 2.240]	0.823 [-0.330, 2.045]
2013–2014	−3.905 [-7.733, −0.132]	−3.176 [-5.532, −0.851]	−0.729 [-2.345, 0.875]	−4.145 [-7.156, −1.191]	−3.064 [-4.905, −1.225]	−0.792 [-2.025, 0.527]
2014–2015	−1.999 [-5.845, 1.835]	−2.254 [-4.598, 0.097]	0.255 [-1.405, 1.905]	0.993 [-1.979, 3.993]	−0.885 [-2.710, 0.943]	1.969 [0.967, 3.092] 3.756 [2.448, 4.806]
2015–2016	1.243 [-2.617, 5.150]	−0.487 [-2.933, 1.975]	1.730 [0.021, 3.456]	3.917 [0.960, 6.950]	0.176 [-1.751, 2.149]	2.051 [1.336, 2.810]
2016–2017	−4.090 [-8.106, −0.154]	−3.986 [-6.664, −1.307]	−0.104 [-2.037, 1.747]	−1.709 [-4.390, 1.016]	−3.882 [-6.197, −1.550]	

Note: This table presents productivity growth estimates based on the fixed and random parameters models, using the translog input stochastic distance frontier within a Bayesian framework. The results report the average annual productivity growth, along with its decomposition into technical change and efficiency change. Credibility intervals at the 5 % level are shown in square brackets.

their methods in customer acquisition, counseling, and retention. These successful techniques were then transformed into standardized protocols and training programs for broader staff implementation.

- Physical Network Optimization: Branches operating with diminishing returns to scale, as identified in the RTS analysis, were resized or closed.
- Process Standardization: Redundancies were eliminated and operations simplified to reduce costs and transaction times. This included the creation of administrative units, such as OPPLUS,[5] to offload lower-value processes from branches.

Essentially, productivity gains arose not from acquiring new capabilities but from the more disciplined and effective use of existing resources.

Under regulatory pressure to increase solvency and the need to restore profitability, investments in operational efficiency offered a more predictable and shorter-term return than higher-risk innovation initiatives. Notably, investments in technological innovation gained momentum in the years following the study period, once the branch network had been optimized. Therefore, the observed patterns in productivity growth reflect the entity's strategic focus during the post-crisis period, where survival and consolidation were prioritized over technological expansion.

5. Conclusions

This paper contributes to the existing literature on bank branches by considering unobserved technological heterogeneity and time-varying efficiency. To do so, we estimated a random parameters model following the study carried out by Feng and Zhang (2014), which could avoid an inconsistent parameter estimation when this randomness is not considered in a panel data stochastic frontier model.

The empirical data from 2011 to 2017 was drawn from branches of a large Spanish commercial bank with different specialities, located in different local markets, and with varying branch size in terms of market share. These branches could have different production functions and time-varying returns to scale (RTS).

Our results, using a translog stochastic distance frontier function estimated in a Bayesian random parameter model, confirm substantial technological heterogeneity across the branch network, a finding with important theoretical and managerial implications.

Below, we briefly describe the theoretical and management implications of our paper.

5.1. Theoretical implications

A random parameters model may be a valuable approach in identifying and modelling time-varying branch-specific inefficiencies that may not be captured by fixed parameters models, and that can be separated for technological heterogeneity. By accounting for the variability and potential importance of certain inefficiency drivers across branches (e.g., market share), the model specification enables a more precise estimation of efficiency and can help distinguish branches based on their unique characteristics. In general, the random parameters model estimated higher efficiencies, but also greater dispersion in the estimates of efficiencies and RTS. Similar

[5] Developed by Operations and Services, SA, OPPLUS focuses primarily on 1) optimizing business processes (back office): It handles operational tasks so that offices can concentrate on their core activities (customer management) and 2) Consulting and advisory services: It provides internal consulting solutions to improve efficiency and quality in business processes.

results were also found by Tsionas (2002) and Feng and Zhang (2014). It is important to consider these unobserved heterogeneities when evaluating efficiency, and the random parameters model appears to be a useful tool in doing so. Therefore, explicitly modeling unobserved heterogeneity is essential to avoid biased assessments of branch performance.

5.2. Practical implications

Results show that, in general, bank branches have high efficiencies but different RTS over time. Branches with increasing RTS predominate during many years of the sample (2013–2017) when considering technological heterogeneity using the random parameters model, but they are not adequately identified by the fixed parameters model. This result indicates that a bank branch's average production cost decreases as its output (e.g., loans, deposits) increases. For instance, if a branch doubles its inputs (such as personnel and technology) and its output (e.g., the number of loans processed) more than doubles, it experiences increasing returns to scale. Finally, bank branch productivity growth varies in the study period, with efficiency change being the main factor that explains the growth.

Using these results, we can describe three management implications. First, managers can focus on the results of random parameters model for the assessment of efficiency and RTS of bank branches in the short term. The results could serve to determine a ranking of inefficient branches as well as for calculation of RTS for all branches. In this way, they can determine at any point of time which bank branches are performing worst. Internal policies to favour constant RTS (which operates at the optimal scale) can be undertaken, provoking increasing scale (IRS) and reducing scale (DRS).

The findings of this study enable the formulation of differentiated internal policy recommendations based on the RTS of each branch. The detected heterogeneity justifies a management approach that is not uniform but tailored to each unit's position along its production path. Based on the empirical analysis, the entity can implement an expansion policy for branches with increasing returns to scale (IRS), guided by two strategic lines of action:

- Commercial Expansion: Implement localized marketing campaigns, cross-selling programs with incentives for branch staff to increase the number of products per customer, and business development initiatives to attract more clients and operations.
- Selective Investment: Provide technology, training, and staff specialization to manage more complex products or serve specific customer segments (e.g., SMEs, personal banking), thereby attracting higher-value and higher-volume business.

Conversely, the detection of decreasing returns to scale (DRS) in a segment of the network indicates that these branches have exceeded their optimal efficient scale, incurring diseconomies of scale. For this group, the analysis suggests a rationalization strategy focused on reducing complexity and optimizing the cost structure through:

- Process Reengineering: Simplifying operations and specializing branches in specific market niches (e.g., managing investment portfolios or complex mortgages) to reduce management overhead. Dedicated HUBs for complex products, such as mortgage transactions, exemplify this strategy.
- Channel Optimization: Promoting digital channels for low-value transactions to decongest physical operations and free up human capital for higher-value advisory tasks. This also leverages digital investments to serve the mass customer segment efficiently and profitably, optimizing the bank's overall service strategy.
- Network Consolidation: Restructuring the branch network through mergers or, if necessary, closures to eliminate costs associated with inefficient scale.

Second, productivity estimators derived from the model enable the entity to adopt a dynamic performance evaluation system that transcends traditional budget variance controls. Specifically, branch efficiency scores can be incorporated into key performance indicators (KPIs) to weight commercial activity not by volume, but by its marginal contribution to the firm's Net Present Value (NPV), considering the type, term, and risk rating of each transaction. This approach aligns managerial incentives with long-term value creation and supports a more efficient allocation of capital and human resources across the network, thereby enhancing competitiveness and sustainability.

Third, the model identifies market share (both loans and deposits) as a key endogenous determinant of efficiency, although its impact varies depending on branch scale. For branches operating with IRS, strategic expansion of market share directly improves efficiency. This can be achieved through competitive commercial policies and by adjusting product offerings—in volume, price, term, and risk—to capture profitable business opportunities.

However, this strategy entails a fundamental trade-off between growth and risk. Aggressive credit expansion may increase market share in the short term but must be carefully managed to maintain portfolio quality and prevent an increase in the non-performing loans (NPLs) ratio, which would negatively impact efficiency. Risk management remains a critical area for any financial institution, ensuring survival and stability. Therefore, management's objective is not simply to maximize market share but to optimize it under rigorous risk constraints, adhering to regulatory capital frameworks (e.g., Basel III/IV) to safeguard long-term sustainability.

Finally, several limitations of this study should be acknowledged. First, the analysis was constrained by data availability, which limited the inclusion of additional covariates and prevented expansion of the database due to difficulties in obtaining branch-level information from the bank. Second, the Bayesian models could be extended by employing alternative prior distributions to model inefficiency, such as truncated normal distributions, representing a potential avenue for future research. Third, future studies could explicitly model the determinants of technological heterogeneity, moving beyond its identification. While the present study successfully establishes the existence and magnitude of this heterogeneity, the next step is to investigate the underlying factors that drive and sustain it, including local market characteristics, branch-specific attributes, and strategic focus.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research has been partially funded by the Project "Economic Evaluation and Meta-Analysis: Bayesian Solutions in Health Economics" (Ref. PID2021-127989OB-I00) financed by Ministry of Science and Innovation, Spanish Government.

Appendix

Table A1
Definitions of variables and sources.

Variable	Definition	Source
Outputs		
y_1: Value of deposits (euros)	Represents the total value of deposits in the bank branch in euros for each year	Profit and loss statements for each branch
y_2: Value of loans (euros)	Represents the total value of loans in the bank branch in euros for each year	Profit and loss statements for each branch
Inputs		
x_1: Number of ATMs	Total number of automated teller machines per branch for each year	Management control department
x_2: Number of full employees	Total number of full employees per branch for each year	Human resources department
x_3: Operational costs (€)	Represents the total value of operational costs in the bank branch in euros for each year	Profit and loss statements for each branch
x_4: Floor space of the branch (in m^2)	Total surface area of each branch for each year	Management control department
Environmental variables		
z_1: Market share of deposits (%)	Represents the relative market size of each bank branch in terms of deposits for a given year. It is calculated as the branch's total deposits divided by the sum of deposits across all branches in that year.	Own calculations
z_2: Market share of loans (%)	Represents the relative market size of each bank branch in terms of loans for a given year. It is calculated as the branch's total loans divided by the sum of loans across all branches in that year.	Own calculations

Note: This table shows the definitions and sources of variables used in our study.

Table A2
Productivity growth using Malmquist-DEA.

Period	Malmquist index summary		
	Average annual productivity growth	Technical change	Efficiency change
2011–2012	6.652	6.319	1.053
2012–2013	1.287	0.786	1.637
2013–2014	1.330	1.364	0.974
2014–2015	1.726	1.530	1.128
2015–2016	1.454	1.395	1.042
2016–2017	1.111	1.646	0.675

Data availability

The data that has been used is confidential.

References

Akhavein, J., Frame, W. S., & White, L. J. (2005). The diffusion of financial innovations: An examination of the adoption of small business credit scoring by large banking organisations. *Journal of Business, 78*(2), 577–596.

Assaf, A. G., & Barros, C. P. (2013). A global benchmarking of the hotel industry. *Tourism Economics, 19*(4), 811–821.

Assaf, A. G., & Magnini, V. (2012). Accounting for customer satisfaction in measuring hotel efficiency: Evidence from the US hotel industry. *International Journal of Hospitality Management, 31*, 642–647.

Assaf, A. G., Matousek, R., & Tsionas, E. G. (2013). Turkish bank efficiency: Bayesian estimation with undesirable outputs. *Journal of Banking & Finance, 37*, 506–517.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management, 17*(1), 99–120.

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

Bartelsman, E., Haltiwanger, J., & Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *The American Economic Review, 103*(1), 305–334.

Battese, G. E., & Rao, D. P. (2002). Technology gap, efficiency, and a stochastic metafrontier function. *International Journal of Business and Economics, 1*(2), 87–93.

Battese, G. E., Rao, D. S. P., & O'Donnell, C. J. (2004). A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. *Journal of Productivity Analysis, 21*, 91–103.

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

Berger, A. N., Miller, N. H., Petersen, M. A., Rajan, R. G., & Stein, J. C. (2005). Does function follow organizational form? Evidence from the lending practices of large and small banks. *Journal of Financial Economics, 76*(2), 237–269.

Cabrera-Suárez, I., & Pérez-Rodríguez, J. V. (2020). Assessing branch efficiency and managerial behaviour in a large Spanish commercial bank. *Spanish Journal of Finance and Accounting, 49*(1), 48–73.

Cabrera-Suárez, I., & Pérez-Rodríguez, J. V. (2021). Bank branch performance and cost efficiency: A stochastic frontier panel data approach. *International Journal of Finance & Economics, 26*(4), 5850–5863.

Camanho, A. S., & Dyson, R. G. (1999). Efficiency, size, benchmarks and targets for bank branches: An application of data envelopment analysis. *Journal of the Operational Research Society, 50*, 903–915.

Camanho, A. S., & Dyson, R. G. (2006). Data envelopment analysis and Malmquist indices for measuring group performance. *Journal of Productivity Analysis, 26*, 35–49.

Canales, R., & Nanda, R. (2012). A darker side to decentralized banks: Market power and credit rationing in SME lending. *Journal of Financial Economics, 105*(2), 353–366.

Caves, D. W., Christensen, L. R., & Diewert, W. E. (1982). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica, 50*, 1393–1414.

Coles, R. A., Goldberg, L. G., & White, L. J. (2004). Cookie cutter vs. character: The microstructure of small business lending by large and small banks. *Journal of Financial and Quantitative Analysis, 39*, 227–251.

Colombi, R., Kumbhakar, S. C., Martini, G., & Vittadini, G. (2014). Closed-skew normality in stochastic frontiers with individual effects and long/short-run efficiency. *Journal of Productivity Analysis, 42*(2), 123–136.

Conner, K. R. (1991). A historical comparison of resource-based theory and five schools of thought within industrial organization economics: Do we have a new theory of the firm? *Journal of Management, 17*(1), 121–154.

Cook, W. D., Harrison, J., Imanirad, R., Rouse, P., & Zhu, J. (2015). Data envelopment analysis with non-homogeneous DMUs. In J. Zhu (Ed.), *International series in operations research & Management science: Vol.221. Data envelopment analysis*. Boston, MA: Springer.

Cortés-García, J. S., & Pérez-Rodríguez, J. V. (2024). Heterogeneity and time-varying efficiency in the Ecuadorian banking sector. An output distance stochastic frontier approach. *The Quarterly Review of Economics and Finance, 93*, 164–175.

Eling, M., & Luhnen, M. (2010). Efficiency in the international insurance industry: A cross-country comparison. *Journal of Banking & Finance, 34*(7), 1497–1509.

Eskelinen, J., Halme, M., & Kallio, M. (2014). Bank branch sales evaluation using extended value efficiency analysis. *European Journal of Operational Research, 232*(3), 654–663.

Feng, G., & Zhang, X. (2014). Returns to scale at large banks in the U.S.: A random coefficient stochastic frontier approach. *Journal of Banking & Finance, 39*(1), 135–145.

Filippini, M., & Greene, W. H. (2016). Persistent and transient productive inefficiency: A maximum simulated likelihood approach. *Journal of Productivity Analysis, 45*(2), 187–196.

Geweke, J. (1992). Evaluating the accuracy of sampling-based approaches to calculating posterior moments. In J. M. Bernardo, J. O. Berger, A. P. Dawid, & A. F. M. Smith (Eds.), *Bayesian statistics 4* (pp. 169–193). Oxford University Press.

Giokas, D. I. (2008). Assessing the efficiency in operations of a large Greek bank branch network adopting different economic behaviors. *Economic Modelling, 25*, 559–574.

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

Goyal, J., Singh, M., Singh, R., & Aggarwal, A. (2019). Efficiency and technology gaps in Indian banking sector: Application of meta-frontier directional distance function DEA approach. *The Journal of Finance and Data Science, 5*(3), 156–172.

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

Greene, W. H. (2008). The econometric approach to efficiency analysis. In H. O. Fried, C. A. K. Lovell, & S. S. Schmidt (Eds.), *The measurement of productive efficiency and productivity change*. New York: Oxford University Press.

Huang, T. H., Lin, Y. C., Huang, K. J., & Liao, Y. W. (2022). Comparing cost efficiency between financial and non-financial holding banks and insurers in Taiwan under the framework of copula methods and metafrontier. *Asia-Pacific Financial Markets, 29*, 735–766.

International Accounting Standards Board. (2014a). *IFRS 9 financial instruments, July*.

International Accounting Standards Board. (2014b). *Project summary: IFRS 9 financial instruments, July*.

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

Koop, G., Osiewalski, J., & Steel, M. F. J. (1997). Bayesian efficiency analysis through individual effects: Hospital cost frontiers. *Journal of Econometrics, 76*, 77–105.

Koop, G., & Steel, M. F. J. (2003). Bayesian analysis of stochastic frontier models. In B. H. Baltagi (Ed.), *A companion to theoretical econometrics* (pp. 520–537). Blackwell Publishing Ltd.

Lambert, P. C., Sutton, A. J., Burton, P. R., Abrams, K. R., & Jones, D. R. (2005). How vague is vague? A simulation study of the impact of the use of vague prior distributions in MCMC using WinBUGS. *Statistics in Medicine, 24*, 2401–2428.

Li, W., Liang, L., Cook, W. D., & Zhu, J. (2016). DEA models for non-homogeneous DMUs with different input configurations. *European Journal of Operational Research, 254*, 946–956.

Los, B., & Verspagen, B. (2000). R&D spillovers and productivity: Evidence from US manufacturing microdata. *Empirical Economics, 25*(1), 127–148.

Los, B., & Verspagen, B. (2006). The evolution of productivity gaps and specialization patterns. *Metroeconomica, 57*(4), 464–493.

Marzec, J., & Osiewalski, J. (2008). Bayesian inference on technology and cost efficiency of bank branches. *Financial markets and institutions*.

Noveiri, M. J. S., & Kordrostami, S. (2022). Meta-frontier stochastic cost and revenue efficiency analysis: An application to bank branches. *International Journal of Information Technology and Decision Making, 21*(6), 1879–1903.

O'Donnell, C. J., & Coelli, T. J. (2005). A Bayesian approach to imposing curvature on distance functions. *Journal of Econometrics, 126*, 493–523.

O'Donnell, C. J., Rao, P., & Battese, G. (2006). Metafrontier frameworks for the study of firm level efficiencies and technology ratios. *Empirical Economics, 34*, 231-225.

Orea, L. (2002). Parametric decomposition of a generalized malmquist productivity index. *Journal of Productivity Analysis, 18*(1), 5–22.

Orea, L., & Kumbhakar, S. C. (2004). Efficiency measurement using a latent class stochastic frontier model. *Empirical Economics, 29*(1), 169–183.

Osiewalski, J., & Marzec, J. (1998). Bayesian analysis of cost efficiency with an application to bank branches. In E. Miklaszewska (Ed.), *Global tendencies and changes in East European banking*. Cracow: Jagiellonian University.

Paradi, J., & Zhu, H. (2013). A survey on bank branch efficiency and performance research with data envelopment analysis. *Omega, 41*, 61–79.
Peteraf, M. A. (1993). The cornerstones of competitive advantage: A resource-based view. *Strategic Management Journal, 14*(3), 179–191.
Rossi, C. V. (1998). Mortgage banking cost structure: Resolving an enigma. *Journal of Economics and Business, 50*, 219–234.
Saloner, G., & Shepard, A. (1995). Adoption of technologies with network effects: An empirical examination of the adoption of automated teller machines. *Random Journal of Economics, 26*(3), 479–501.
Tecles, P. L., & Tabak, B. M. (2010). Determinants of bank efficiency: The case of Brazil. *European Journal of Operational Research, 207*(3), 1587–1598.
Tsekouras, K., Chatzistamoulou, N., & Kounetas, K. (2017). Productive performance, technology heterogeneity and hierarchies: Who to compare with whom. *International Journal of Production Economics, 193*, 465–478.
Tsionas, E. G. (2002). Stochastic frontier models with random coefficients. *Journal of Applied Econometrics, 17*, 127–147.
Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal, 5*(2), 171–180.
Williams, J. (2004). Determining management behaviour in European banking. *Journal of Banking & Finance, 28*(10), 2427–2460.