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EFFICIENCY IN PUBLIC HIGHER EDUCATION: A STOCHASTIC FRONTIER ANALYSIS CONSIDERING HETEROGENEITY

EFICIENCIA EN LA EDUCACION PUBLICA SUPERIOR: UN ANALISIS DE FRONTERA ESTOCASTICA CONSIDERANDO HETEROGENEIDAD

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Abstract

We aim to study technical efficiency of undergraduate teaching activity in national (public) universities in Argentina. We employ a stochastic frontier analysis (SFA) with a panel of 37 national universities over 2005-2013. We compare models that do not account for heterogeneity with heterogeneity-extended SFA models. We find from 18 percent to 25 percent of inefficiency on average in terms of lost outcomes (graduates) depending on the specification, with high dispersion among universities. Models considering heterogeneity report the highest levels of technical efficiency. Besides, the results show evidence of heterogeneity both observed and unobserved. Our estimates are robust to different specifications.

Keywords: *Universities' Teaching Efficiency, Stochastic Frontier Analysis, Heterogeneity*

JEL Classification: *I23, C23.*

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Resumen

Nuestro objetivo es estudiar la eficiencia técnica de la educación de grado en universidades nacionales (públicas) en Argentina. Empleamos un análisis de frontera estocástica (SFA) con un panel de 37 universidades nacionales durante 2005-2013. Comparamos modelos que no tienen en cuenta la heterogeneidad con modelos extendidos de SFA con heterogeneidad. Encontramos desde el 18 al 25 por ciento de ineficiencia en promedio en términos de resultados perdidos (graduados) dependiendo de la especificación, con alta dispersión entre las universidades. Los modelos que consideran heterogeneidad muestran los niveles más altos de eficiencia técnica. Además, los resultados muestran evidencia de heterogeneidad tanto observada como no observada. Nuestras estimaciones son robustas a diferentes especificaciones.

Palabras clave: *Eficiencia en la Educación Universitaria, Análisis de Frontera Estocástica, Heterogeneidad*

Clasificación JEL: *I23, C23*

1. INTRODUCTION

Higher education coverage has increased in recent years in Latin America and the Caribbean. The average gross enrollment rate in higher education (within population ages 18-24) in the region grew from 21 to 43 percent between 2000 and 2013. The expansion occurred at a time of economic growth, abundance of fiscal resources and middle class rise, and it was concentrated in the low- and middle-income segments. Completion rates in the Latin American region are close to 50 percent (compared to around 65 percent in the United States). Lower income and lower ability students are more likely to drop out. Time to degree in Latin America is 136 percent of the stipulated time (similar than the United States figure). Nevertheless, the average statutory duration of the programs is shorter in the United States than in Latin America. Student/faculty ratio is similar in Latin America to that of comparable countries of Eastern Europe or Eastern Asia, while salaries represent a higher proportion of total universities' expenses in Latin America (Ferreyra et al., 2017).

In Argentina, the public and private sector share the supply of higher education. The public institutions are mostly federal, and the private universities are non-for-profit organizations (mostly foundations). Law No. 24521 of 1995 of superior education established a National State responsibility in financial support for national universities with federal revenues. National universities have economic and financial autonomy; they manage their resources and approve their budget with considerable freedom in their administrative, planning, and academic activities.

The Argentine educational system does not include standardized exams, neither to complete high school nor to access public universities or to fulfill university degrees. Moreover, tuition is free for all undergraduate students attending public universities, regardless of their financial status and academic achievements.

The demographics of the country results in a strong concentration of students and universities in the metropolitan area of the nation. In the last thirty years, several universities have been created in the suburbs of the capital city to de-congest one of the oldest and largest universities of the country, the University of Buenos Aires (UBA).[1]

According to data of the Ministry of Education of Argentina, in 2016 there were 57 public universities, 49 private institutions (all non-for profit), 4 provincial and 1 foreign university. In 2015 there were 1.9 million undergraduate students in Argentine universities, where 1.49 million attended public universities. In that year, there were over 458 thousand new enrolling students and 125 thousand undergraduates obtained their degrees. Between 2006 and 2015, the stock of students increased 19 percent, enrollment rate grew 27 percent and 47 percent more students concluded studies. Nevertheless, only 27 percent of the students completed their studies in the stipulated time in public universities, while 37 percent dropped-out during the first year.

The heterogeneity among public universities is another characteristic of the Argentine national system. For example, over the period 2005-2013, the mean degree rate (defined as the number of graduated/(0.2*number of students)) was 0.26 for the whole country, but this indicator shows a strong dispersion within the nation. For instance, the rate goes from 0.39 in the University of Rosario (located in the central region of Argentina) to 0.07 in the University of Jujuy (that is in the northwest part of the country).

The system is characterized by high university dropout rates, long duration of the studies, low graduation rates and, in some disciplines difficulty in finding a suitable job is reported. Colomé (1996) highlights the scarce academic complementarity of institutions within the system, being the student mobility more an administrative matter than an academic issue. Among national universities located at short distances, there is overlapping in the degree programs offered.

The measurement of efficiency in higher education institutions in Argentina has gained growing interest in recent years, especially due to the expansion of the university system. This expansion has been supported by two phenomena: the creation of new public universities and, the growth in the resources that the National State allocates to education. In fact, Law No. 26075 of 2005 of Education Financing established

[1] The UBA was founded in 1820 and is the second oldest public university in the country. According to data of the Ministry of Education of Argentina, 25 percent of the students of public universities attend the UBA, while its budget represented almost 32 percent of total expenses allocated to public universities over the period 2003-2015 (*Anuarios de Estadísticas Universitarias*, available at: http://portales.educacion.gov.ar/spu/investigacion-y-estadisticas/anuarios/).

that by 2010 the resources allocated to all education levels have to be equivalent to 6 percent of the Gross Domestic Product, including higher education.

In this context, it is relevant to analyze the results of the educational process in terms of the product achieved compared to the inputs used. In particular, as public financial resources are involved in the educational process, the study of efficiency is crucial. In this sense, the educational process may be considered as the result of a production process that uses a variety of inputs to yield one or more outputs. The outcomes (or outputs) produced in a university can be split in teaching (knowledge dissemination), research (knowledge production), and extension / transfer / public / community or "third mission" services (externalities and public goods directed to varied audiences beyond campuses) (Cohn and Cooper, 2004; Johnes and Johnes, 2009).

Optimizing producers get the maximum attainable output for a given technology and level of inputs (or, equivalently, they attain given output with the minimum level of inputs). Such optimal relationship between inputs and outputs defines the production possibility frontier. The potentially sub-optimal behavior of a producer is modelled using the concept of technical efficiency. Consequently, the efficiency of a university is defined as the capacity to generate the maximum output given the quantity of inputs they use. The main approaches used for the estimation of the production frontier are the Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA).

In the case of Argentina, the combination of increasing public resources supporting public universities, the historically low completion rates observed and, the heterogeneity among universities, support the importance of studying efficiency in higher education.

The aim of this paper is to estimate technical efficiency for undergraduate teaching activity in national universities in Argentina using SFA. As detailed in Section 2, there are several papers that work with production frontier-type applications to higher education in the international literature. However, there are very few studies for Argentina.

Our paper contributes to the literature in two main aspects. First, we make the first quantitative estimation of technical efficiency in higher public education system in Argentina as a whole, using SFA. Second, we concentrate on modeling university specific observed and unobserved heterogeneity, to estimate technical efficiency more accurately, and we include a sensitivity analysis to check for the robustness of our results. If heterogeneity is not considered, it can create considerable bias in the inefficiency estimates as far as the models do not consider the specific differences among universities.

The paper is organized as follows: Section 2 accounts for the literature review on universities' efficiency; Section 3 depicts the methodology and data used; Section 4 shows the estimation results and the sensitivity checks; and finally, Section 5 presents the conclusions of the study.

2. LITERATURE REVIEW

The existent studies vary in the definitions of the variables used to reflect inputs and outputs, and in the methods they use to appraise efficiency. Most conclude that inputs can be grouped as student inputs, staff inputs and capital inputs, while outputs can be divided into teaching and research (Johnes and Yu, 2008).

Teaching is the delivering of educational services, which implies human capital accumulation, including both knowledge, competences, and skills. The main variables used in the literature to approximate the teaching activity are: (i) the number of degrees completed, which is the most precise measure even when it may underestimate the outcomes because of dropouts (Avkiran, 2001; Worthington, 2001; Salerno, 2003, Johnes, 2006b; Alberto, Carignano and Ercole , 2010; Katharaki and Katharakis, 2010; Coria, 2011; Kuah and Wong, 2011; Laureti, Secondi and Biggeri, 2014; Cantele, Guerrini and Campedelli, 2016; Quiroga-Martinez, Fernández-Vázquez and Alberto, 2018); (ii) the results in standardized exams, recalling that student´s grade is a complex function of the student´s entry-level ability, the marking standards of the university, as well as of teaching and supervision quality (Worthington, 2001; Johnes, 2006b; Kuah and Wong, 2011; Zoghbi, Rocha and Mattos, 2013; Laureti, Secondi and Biggeri, 2014); (iii) the number of students, which is in fact an indicator of the "raw material" of the process (Salerno, 2003; Cantele, Guerrini and Campedelli , 2016); (iv) courses/hours/credits taught (Cohn and Cooper, 2004; Kuah and Wong, 2011); (v) job or remuneration attainment once graduated (Worthington, 2001; Kuah and Wong, 2011; Zoghbi, Rocha and Mattos, 2013); (vi) admission to graduate studies (Ferreyra et al., 2017) and; (vii) products, such as training to non-graduated students (Coria, 2008).

Meanwhile, research is the development and accumulation of new knowledge. This output can be approximated by: (i) published products (Salerno, 2003; Worthington and Lee, 2008; Coria, 2011; Kuah and Wong, 2011; Cantele, Guerrini and Campedelli, 2016); (ii) citation indexes (Avkiran, 2001; Kao and Hung, 2008); (iii) Ph.D. awarded (Worthington and Lee, 2008; Kuah and Wong, 2011; De Fraja and Valbonesi, 2012); (iv) patents and other intellectual property issues (Kao and Hung, 2011; Kuah and Wong, 2011); (v) grants or other funds for projects (Abbott and Douccouliagos, 2003; Salerno, 2003; Katharaki and Katharakis, 2010; Kuah and Wong, 2011; Cantele, Guerrini and Campedelli, 2016; Kao and Hung, 2016), which can be considered more properly as inputs than as outputs (Johnes and Yu, 2008).

Extension (also called Transfer / Public or Community Services or Third Mission) consists in the generation of public goods and externalities, with possible (but difficult to measure) rewards in terms of publicity and prestige, in higher tuition values or in supporting fundraising activities. Extension includes cultural and sports activities (Avkiran, 2001; Cohn and Cooper, 2004), non-formal education for the elder and other collectives (Cohn and Cooper, 2004, Worthington and Lee, 2008), informed opinion and advice on social or community issues (Avkiran, 2001; Cohn and Cooper, 2004) and the most difficult to measure, the construction of (desirable) social values and citizenship (Avkiran, 2001; Ferreyra et al., 2017). Due to the difficulties in measuring extension activities, their effects on university efficiency have not yet been estimated in the empirical literature.

The resources (inputs) of university education can be classified as human and non-human resources. The former includes labor and "raw materials", and the latter encompasses facilities. Human resources are academic and non-academic staff (Johnes, 1996; Avkiran, 2001; Worthington, 2001; Worthington and Lee, 2003; Johnes and Yu, 2008; Coria, 2011; Kuah and Wong, 2011; Laureti, Secondi and Biggeri, 2014), while the "raw materials" of the process are the students (Coria, 2011; Laureti, Secondi and Biggeri, 2014). To address the possible substitution between teaching and research activity, it can be calculated the ratio between research teachers (or research workload) and total faculty (Johnes and Yu, 2008; Kao and Hung, 2008; Coria, 2011). Alternatively, salaries can be used to approximate human inputs (Coria, 2011). Non-human resources include capital goods and materials, which can be measured by using physical units such as square meters of laboratories or classrooms, classroom seats, computers and books in libraries (Johnes, 1996; Laureti, Secondi and Biggeri, 2014; Cantele, Guerrini and Campedelli, 2016) or by money spent on hardware (Worthington, 2001; Cao and Hung, 2008; Worthington and Lee, 2008).

Quality variables are used in some university efficiency studies. Quality can be considered either as an outcome or as an input, using ratios or dummy variables. These variables are usually indications of completion (Zogbi, Rocha and Mattos, 2013; Ferreyra et al., 2017), achievements and recognition (duration, structure and contents of the programs, time dedication and qualification of the staff). Quality can also be applied to the expenditures (Ferreyra et al., 2017). It can also be addressed by the technology in use, for example by establishing the ratio between on-line and off-line students (Wolff, Baumol and Noyes Saini, 2014). The quality of the staff input is reflected by the faculty proportion with professor status, and/or full-time on part-time professor's ratio (Kuo and Ho, 2003; Johnes and Yu, 2008; Sav, 2012). The premise underlying this variable is that the promoted/tenured faculty is more productive than the others. Nevertheless, they may have been promoted when research demands were less strict than nowadays or, once promoted, professors could be less motivated and less productive which results in an uncertain effect of the staff status (Johnes and Yu, 2008).

Finally, environmental, or contextual variables allow for unbiased comparisons among institutions and permit addressing for observable heterogeneity. They are used for separating the effect of uncontrollable inputs. It can be distinguished at least three groups of environmental variables in the literature: (i) those referred to students' intellectual, economic, and social background (Worthington, 2001; Zoghbi, Rocha and Mattos, 2013; Laureti, Secondi and Biggeri, 2014; Ferreyra et al., 2017) ; (ii) those referred to sociodemographic characteristics as poor or rich regions in term of GDP and human capital (Costa, de Sousa Ramos and Ramos de Sousa, 2011; Laureti, Secondi and Biggeri, 2014; Cantele, Guerrini and Campedelli, 2016; Ibañez Martín, Morresi and Delbianco, 2017), ethnicity (Worthington, 2001), age (Laureti , Secondi and Biggeri, 2014), or gender (Johnes, 2006a; Laureti, Zoghbi, Rocha and Mattos, 2013; Secondi and Biggeri, 2014) and; (iii) those referred to the type of university -big or small- (Laureti, Secondi and Biggeri, 2014; Daraio, Bonaccorsi and Simar, 2015; Cantele, Guerrini and Campedelli, 2016), old or new (Johnes and Johnes, 2009), private or public (Millot 2015; Cantele, Guerrini and Campedelli, 2016), profit or non-for profit, laic or religious, specialized or generalist, specialized in "labor intensive" or in "capital intensive" disciplines (Cohn and Cooper, 2004; Horne and Ho, 2008; Johnes and Johnes, 2009; Laureti, Secondi and Biggeri, 2014; Daraio, Bonaccorsi and Simar, 2015; McGukin and Winkler, 2015; Cantele, Guerrini and Campedelli, 2016).

Previous works on this issue for Argentina are Alberto, Carignano and Ercole (2010) who rank the universities using a cross efficiency model, Coria (2011) who finds that, for all public universities, the average level of inefficiency varies from 23.2 percent to 23.9 percent, Ibañez Martín, Morresi and Delbianco (2017) who estimate inefficiency for the departments of one specific national university of Argentina and Quiroga-Martínez, Fernández-Vázquez and Alberto (2018), who find an average efficiency of 78.6 percent among the public universities of the country. Three of these studies use a non-parametric method (Data Development Analyst –DEA) to estimate efficiency in public universities, while Ibañez Martín, Morresi and Delbianco (2017) apply a parametric stochastic frontier analysis (SFA). Quiroga-Martinez, Fernández-Vázquez and Alberto (2018) estimate a two stage DEA.

3. METHODOLOGY AND DATA

3.1. Stochastic Frontier Analysis

To estimate technical efficiency, we employ one of the most used parametric techniques, namely stochastic frontier analysis (SFA).[2] In particular, we include university specific heterogeneity in the SFA to account for the potential bias in the inefficiency estimates.

[2] The other most used frontier efficiency technique is Data Envelopment Analysis (DEA). This non-parametric method characterizes the set of efficient producers (those on the frontier) and then derives estimates of inefficiency based on how far each observation deviates from the frontier. Both methods have advantages and disadvantages. For example, SFA requires ample samples and yields the possibility of statistical tests of the results. DEA allows working with relatively small samples, but in its common formulation it does not allow testing the statistical significance of the results. SFA estimates a function, thence crucial decisions should be made with respect to the functional form that describes the phenomena and to the distribution of the error term. Those decisions are not required in the DEA analysis, nevertheless, the inefficiency scores it yields are deemed as purely inefficiency without considering randomness at all.

Prior to the estimation of the stochastic frontier (SF), we examine the empirical form of the production function, i.e., the empirical association between the number of graduates (Y_{it}) of university *i* at year *t* and the explaining variables (included in the vector D_i for dummy variables and in X_{it} for the other independent variables). We also include a time-trend variable τ to capture the technological change over time. Based on the Box Cox transformation method (Box and Cox, 1964), we perform alternative transformations to the variables in the model to capture the form of the relationship.[3] The general specification of the regression has the following form:

$$Y_{it}^{(\theta)} = \alpha + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + \varepsilon_{it} \qquad i = 1,\ldots,N,\ t=1\ldots T \qquad (1)$$

where $Y_{it}^{(\theta)} = \frac{Y_{it}^{\theta} - 1}{\theta}$ and $X_{it}^{(\lambda)} = \frac{X_{it}^{\lambda} - 1}{\lambda}$ are the vectors of the dependent and the independent variables subject to transformations for specific values of the parameters λ and θ if $\theta, \lambda \neq 0$, and $Y_{it}^{(\theta)} = \log(Y_{it})$, $X_{it}^{(\lambda)} = \log(X_{it})$ are the transformations when $\theta = 0$ and $\lambda = 0$, respectively.[4]

This Box Cox general functional form includes the most common model specifications as subsets, including linear, semi-log and double log. Then, using Pooled Ordinary Least Squared (POLS), we estimate Eq. (1) using the following alternative specifications: linear (θ=λ=1), log-lin (θ=0, λ=1), lin-log (θ=1, λ=0) and log-log (θ=λ=0). It is important to note that the last model produces the Cobb–Douglas production function.

Secondly, to select the most appropriate specification within the set of candidate models, we perform the Bayesian Information Criteria (BIC). The BIC is defined as: BIC = – 2logL + log(N)K, where L is the likelihood of the model, N is the number of observations in the dataset and K is the number of parameters to be estimated in the model. The BIC rewards goodness of fit (as assessed by the likelihood function) and penalizes the number of estimated parameters. The model with the minimum BIC value is considered the model that better fits the data.[5]

Thirdly, with the selected specification for Eq. (1), we estimate the stochastic production frontier. In the SFA the residual ε_{it} is defined as the difference between

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[3] The Box and Cox transformations are a family of power transformations used in statistics to correct biases in the error distribution, to correct unequal variances and mainly to correct the nonlinearity in the relationship. In this paper we focus on powers usually used to characterize production relationships.

[4] The notation $Y_{it}^{(\theta)}$ and $X_{it}^{(\lambda)}$ (with θ and λ in parentheses) indicates that the vectors of dependent and independent variables are transformed using those parameters. The specific transformations are defined as $\frac{Y_{it}^{\theta} - 1}{\theta}$ and $\frac{X_{it}^{\lambda} - 1}{\lambda}$, respectively.

[5] To make the BIC criteria comparable among the different models, we use the likelihood of log-normal distribution instead of the likelihood of the normal distribution in the BIC formula for the independent variable Y_{it}. This adjustment was performed in the models where the response variable is $\log(Y_{it})$ (see, Burnham and Anderson, 2002 p.81).

the normally distributed term v_{it}, which represents the classical random error $\left(v_{it} \sim iid\ N\left(0,\ \sigma_v^2\right)\right)$, and a one-sided disturbance u_{it} which represents inefficiency:

$$\varepsilon_{it} = v_{it} - u_{it} \qquad i = 1,\ldots,\mathrm{N},\ t=1\ldots\mathrm{T} \qquad (2)$$

It is also assumed that v_{it} and u_{it} are independent from each other and identically distributed across observations. The SFA models are estimated via maximum likelihood (ML) or simulated maximum likelihood (SML) techniques and it is usually assumed that the distribution of u_{it} is half-normal, truncated normal, exponential, or normal gamma.[6]

According to Aigner, Lovell and Schmidt (1977), technical efficiency (TE) is a measure of how well the individual transforms inputs into a set of outputs based on a given set of technology and economic factors. If TE is defined as the ratio of observed output to the stochastic frontier output, then $TE_{it} = \exp(-u_{it})$.[7] As the econometric procedure allows to estimate ε_{it} (i.e, the compound error of Eq. (1)), we use the strategy proposed by Jondrow, Lovell, Materov and Schmidt (1982), hereafter JLMS, to decompose the inefficiency term from the residual. A point estimate of the inefficiencies can be obtained using the mean:

$$E\left(u_{it} \diagdown \varepsilon_{it}\right) = \frac{\sigma_* \ \phi(\frac{\mu_{*it}}{\sigma_*})}{\Phi(\frac{\mu_{*it}}{\sigma_*})} + \mu_{*it} \qquad i = 1,\ldots,\mathrm{N},\ t=1\ldots\mathrm{T} \qquad (3)$$

where $\mu_{*it} = \dfrac{-\sigma_u^2\ \varepsilon_{it}}{\sigma_v^2 + \sigma_u^2}$ and $\sigma_*^2 = \dfrac{\sigma_u^2\ \sigma_u^2}{\sigma_v^2 + \sigma_u^2}$

For the estimation of TE, we concentrate on SF models that account for universities' heterogeneity. In this case, different academic contents and/or processes, regional differences in socio-economic characteristics of the students and teachers, and geographical features that prioritize some fields over others (such as Agronomics in regions whose productive activity is more linked to agriculture) are aspects that are beyond the universities' authorities control and that could affect their productive

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[6] In general, SFA is based in two sequential steps: in the first, estimates of the model parameters are obtained by maximizing the log-likelihood function. In the second step, point estimates of inefficiency can be obtained through the mean (or the mode) of the conditional distribution $f = (u_i \diagdown \widehat{\varepsilon_{it}})$. For details, see Belotti et al. (2012).

[7] $ET_{it} = \dfrac{f\left(X_{it}\beta\right)\exp(v_{it} - u_{it})}{f\left(X_{it}\beta\right)\exp(v_{it})} = \dfrac{1}{\exp(u_{it})} = \exp(-u_{it})$. If u_{it} equals zero, then TE equals one, and production is said to be technically efficient.

efficiency. If that heterogeneity is not accounted for, it remains in the error term, and the endogenous independent variables would be correlated with the residual violating a basic assumption of the SFA. This would result in biased parameter estimates in the production frontier, including the efficiency estimates.

In this sense, we take heterogeneity into account through the inclusion of those effects in the mean of the distribution of inefficiency (observed heterogeneity) and by randomizing some parameters of the stochastic frontier model (unobserved heterogeneity). We also estimate a combined model where we have randomized the frontier constant term and at the same time explained the mean of the inefficiency distribution by a covariate. We also estimate the "true fixed effects model" (Greene 2005a), where the unobserved heterogeneity is represented by the individual fixed effects. We next include a description of the SFA models used in the empirical strategy that deal with heterogeneity.

3.1.1. Observed heterogeneity

Random Effect models (RE and REH)

We perform the random effect (RE) model proposed by Pitt and Lee (1981) using the linear or nonlinear specification chosen in the first step of the empirical strategy. This means that, although we continue with the notation of the general specification of the production function, the parameters λ and θ take specific values at this stage of the empirical strategy. Then, the RE model is specified as:

$$Y_{it}^{(\theta)} = \alpha + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + \varepsilon_{it} \qquad i = 1,\ldots,\mathrm{N},\ t=1\ldots\mathrm{T} \tag{4}$$

$$\varepsilon_{it} = v_{it} - u_i$$

$$v_{it} \sim \mathrm{N}(0,\sigma_v^2)$$

$$u_i \sim \mathrm{N}^+(0,\sigma_u^2)$$

Or:

$$Y_{it}^{(\theta)} = \alpha_i + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + v_{it} \qquad i =1,\ldots,\mathrm{N},\ t=1\ldots\mathrm{T} \tag{5}$$

where $\alpha_i \equiv \alpha - u_i$

This model fits by ML; it assumes that technical inefficiency is half normal, and that, in proportional terms, it is constant over time. As can be seen, individual heterogeneity cannot be distinguished from inefficiency. Then, the whole time-invariant heterogeneity is confounded into inefficiency, and therefore, $\widehat{u_i}$ might be picking up heterogeneity in addition to, or even instead of, inefficiency (Greene, 2005b). Besides, Kumbhakar and Hjalmarsson (1993) argued that the time varying component v_{it} would inappropriately capture time varying inefficiency.

This specification assumes that inefficiency is not correlated with the regressors, and this is a problem when, in the presence of heterogeneity, the inefficiency term is not independent of the frontier inputs (endogeneity). One way to deal with this issue is to introduce the exogenous variables in the location of the distribution of the inefficiency. The most common approach is to parameterize the mean of the pre-truncated inefficiency distribution.[8] This model specification, called here random effect with observed heterogeneity (REH) model can be written as:

$$
\begin{aligned}
&Y_{it}^{(\theta)} = \alpha + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + \varepsilon_{it} \qquad i=1,\ldots,\mathrm{N},\ t=1\ldots\mathrm{T} \qquad (6)\\
&\varepsilon_{it} = v_{it} - u_i\\
&v_{it} \sim \mathrm{N}(0,\sigma_v^2)\\
&u_i \sim \mathrm{N}^+(\mu_i,\sigma_u^2)\\
&\mu_i = z_0 + z_1 h_i
\end{aligned}
$$

In the case that heterogeneity also depends on time, the vector of explanatory variables associated with technical inefficiency also varies over time and so the mean of the truncated distribution of the inefficiency term.[9] One advantage of this technique is that the correlation between the variables that explain the inefficiency and the independent variables is allowed. However, although observed heterogeneity is modeled separately, unobserved heterogeneity remains in the inefficiency term. And this could result in biased parameter estimates, including the TE. To overcome these limitations, Greene (2005a) proposes the following models which deals with unobserved heterogeneity.

3.1.2. Unobserved heterogeneity

True Fixed Effects Model

To overcome the problem of the previous models where inefficiency cannot be separated from time-invariant individual effects, Greene (2005a) proposes the following model, called the true fixed effects model (TFE), where the university specific constant term is included in the stochastic frontier:

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8 An alternative approach to analyzing the effect of exogenous variables on inefficiency is to rescale its distribution allowing observable variation in σ_{ui}^2. See for example, Caudill and Ford (1993); Caudill, Ford, and Gropper (1995), and Hadri (1999).

9 For more details, see Batesse and Coelli (1995).

$$Y_{it}^{(\theta)} = \alpha_i + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + \varepsilon_{it} \qquad i=1,\ldots,N,\ t=1\ldots T \qquad (7)$$
$$\varepsilon_{it} = v_{it} - u_{it}$$
$$v_{it} \sim N(0,\sigma_v^2)$$
$$u_{it} \sim N^+(0,\sigma_u^2)$$

This model allows controlling for constant individual unobserved heterogeneity and assumes that inefficiency is time varying, meaning that there is not structural inefficiency that persists over the period of analysis. The model is fit by ML and the normal-half normal model is applied to the stochastic part of the regression.

True Random Effects Model

The true random effect model (TRE) proposed by Greene (2005a) is an extension of the previous RE model and has the following structure:

$$Y_{it}^{(\theta)} = \alpha + w_i + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + \varepsilon_{it} \qquad i=1,\ldots,N,\ t=1\ldots T \qquad (8)$$
$$\varepsilon_{it} = v_{it} - u_{it}$$
$$v_{it} \sim N(0,\sigma_v^2)$$
$$u_{it} \sim N^+(0,\sigma_u^2)$$

As can be seen, it is a model with a traditional random effect w_i but with the additional feature that the time varying disturbance is not normally distributed. The model is estimated by maximum simulated likelihood. It is assumed that $w_i \sim N(0,\theta^2)$, where θ represents the standard deviation of the unobserved heterogeneity and $E\left(w_i \diagdown X_{jit}\right) = 0$, where j is the number of independent variables.

Compared with the Pitt and Lee (1981) model where u_i is the inefficiency, in the TRE u_{it} is the inefficiency, and it is time varying. Moreover, whereas in the RE model the inefficiency term also contains all other time invariant unmeasured sources of heterogeneity, in the TRE model these effects appear in w_i and u_{it} picks up the inefficiency.

3.1.3. Observed and unobserved heterogeneity combined

To account for observed and unobserved heterogeneity, it is possible to combine the previous RE and TRE models as follows:

$$Y_{it}^{(\theta)} = \alpha + w_i + \beta X_{it}^{(\lambda)} + \delta D_i + \theta\tau + \varepsilon_{it} \qquad i=1,\ldots,N,\ t=1\ldots T \qquad (9)$$

$$\varepsilon_{it} = v_{it} - u_{it}$$
$$v_{it} \sim \mathrm{N}(0,\sigma_v^2)$$
$$u_i \sim \mathrm{N}^+(\mu_i,\sigma_u^2)$$
$$\mu_i = z_0 + z_1 h_i$$
$$w_i \sim \mathrm{N}(0,\sigma_w^2)$$

With this specification, observed heterogeneity is included in the model by parameterizing the mean of the inefficiency distribution, and the unobserved heterogeneity (which remains in the inefficiency term in the RE model), is accounted for by introducing the specific random effects and by assuming that the inefficiency component varies across individuals and time. Once again, the heterogeneity term could also depend on time, and so, the mean of the truncated distribution of the inefficiency term.

3.2. Data

We work with the "*Anuarios de Estadísticas Universitarias"* of the Ministry of Education of Argentina. We use a balanced panel of 37 National Universities in Argentina with information over the period 2005-2013. The year of foundation was the main criterion followed to choose the Universities of the panel, together with the availability of consistent and continuous information (see Table 5). The newest Universities were not included since the time to "generate" graduates is not long enough. Two universities were not included in the date set since the information was not completed over the period under analysis.[10] The period begins in 2005, when Law No. 26075 of Education Financing was established.

In the literature review we present an exhaustive enumeration of possible variables to address outputs, inputs, quality, and environmental variables. The availability of data forces us to use certain variables and to disregard others. For example, concerning output, variables which characterize the future career of graduates or their achievements as students (such as salary or other labor market achievements, or effective length of studies by cohort, or average grades) are not available. The same happens for results of research activity, such as published papers or registered patents.

As regards inputs, some limitations arise when addressing the quality of the faculty. For example, we can distinguish positions, such as full professor –"titular"-

[10] The National Universities that were not included are: Instituto Universitario del Arte (1996), Noroeste de la Provincia de Buenos Aires (2002), Chaco Austral (2007), Río Negro (2008), José C. Paz (2009), Moreno (2009), Oeste (2009), Villa Mercedes (2009), Arturo Jauretche (2010), Avellaneda (2010) and Tierra del Fuego (2010).

or associate, but we cannot determine if they have any Ph.D.; or we can distinguish full-time from part-time professors, but we do not know if the full-time faculty devote their time to research or to administrative tasks.

The consideration of heterogeneity is important. It also allows addressing some differences among universities. For example, Medicine schools are rarely present in the newest universities. The oldest universities (those founded prior to the 1970s) offer in general more diverse and complex disciplines and they are more research oriented. In fact, Argentina has four scientists awarded with the Nobel Prize in sciences, and all of them worked at the National University of Buenos Aires (UBA).

The output variable is measured as the number of graduates. This variable is defined as the number of undergraduate students who completed all courses and other academic requirements.

The inputs that we consider are students, human resources (faculty), financial resources, and environmental variables. We include the number of students defined as enrolled undergraduates. As human resources, we take the number of teachers, considering their role (professor or assistant) and their time contractual dedication ("exclusive", "semi-exclusive" or "simple"). We calculate a professor variable (Professor_w) and an assistant variable (Assistants_w), in both cases weighting roles with time dedication. Following the Ministry of Education definition for the equivalent full-time ("exclusive") faculty position, the weights are 1 for "exclusive", 0.5 for "semi-exclusive" and 0.25 for "simple". Then, the faculty roles (professor or assistant) are converted into full-time equivalent.

Concerning financial resources, we consider total annual expenditures (i.e. costs of personnel, goods and services and monetary transfers) in constant terms (basis 2013=100).[11] Personnel expenses refer to the remuneration of all salaries, employer contributions, family allowances, extraordinary services and social benefits received by the agents, while the rest of the costs are the operating and capital expenditures.

As the local context influences the development of the educational process in universities, we include dummy variables for the country's five regions defined by the Census Bureau *INDEC* (Metropolitan Buenos Aires –GBA-, Northwest –NOA-, Northeast -NEA-, West –Cuyo-, Central –Pampeana- and Southern –Patagonia-) to capture this effect. Finally, we include a measure of efficiency in the efficiency equation, defined as the ratio number of students of university *i* in period *t* divided into the maximum number of students of university *i* over the period 2005-2013 (rprodst).

Table 1 presents a description of these variables by university. On average, the set of universities considered has 1.29 million students, 66,371 graduates per year, 25,791 full-time equivalent professors and 28,393 full time equivalent assistants. Considering a mean duration of five years for each degree, the graduation rate is 25.7 percent (66,371/258,234) on average. Each year, the financial resources employed

[11] To deflate the expenditure series, we use the ICC Index calculated by INDEC.

by the sample of universities averaged ARS 42,633 million in terms of 2013 constant prices (equivalent to 7,909 million dollars at July 1st). [12] Then, each graduate demanded on average ARS 642,000 (or USD 119,000) of financial resources. Table 2 presents the descriptive statistics of the whole sample.

TABLE 1

RESOURCES AND OUTCOMES BY UNIVERSITY (AVERAGE 2005-2013)

University	Graduates	Students	Exclusive	S-exclusive	Simple	Professors_w	Assistants_w	Expenditures	Rprodst
Buenos Aires *(1821), GBA*	16,809	322,535	2,392	2,871	18,786	3,025	5,499	13,500	0.90
Catamarca *(1972), NOA*	388	12,379	306	402	385	443	160	811	0.94
Centro PBA *(1974), Pampeana*	585	12,425	563	386	854	491	478	1,050	0.90
Chilecito *(2004), NOA*	48	3,066	44	118	161	99	44	166	0.52
Comahue *(1971), Patagonia*	957	26,997	587	748	1,348	597	701	1,440	0.87
Cuyo *(1939), Cuyo*	2,305	31,322	661	1,942	1,695	1,177	879	2,300	0.99
Córdoba *(1613), Pampeana*	6,875	106,413	1,371	3,275	4,334	1,973	2,118	4,340	0.96
Entre Ríos *(1973), Pampeana*	913	13,043	190	976	1,054	504	438	467	0.88
Formosa *(1988), NEA*	563	11,691	97	331	730	280	165	249	0.92
Gral. Sarmiento *(1993), GBA*	196	5,145	234	88	0	137	141	212	0.72
Jujuy *(1972), NOA*	184	12,864	208	499	403	275	283	510	0.87
La Matanza *(1989), GBA*	1,308	31,184	448	738	444	387	541	811	0.86
La Pampa *(1958), Pampeana*	410	8,953	261	345	1,078	334	369	435	0.97
La Plata *(1897), Pampeana*	4,953	99,699	1,507	2,138	8,911	1,833	2,971	2,760	0.89
La Rioja *(1994), NOA*	603	24,034	54	908	727	405	285	367	0.75
Lanús *(1995), GBA*	472	10,355	38	159	256	144	38	207	0.81
Litoral *(1919), Pampeana*	1,664	39,184	649	1,083	1,878	767	894	1,050	0.89
Lomas de Zamora *(1972), GBA*	2,699	34,735	104	138	2,711	504	346	408	0.93
Luján *(1972), GBA*	895	16,889	286	418	840	326	380	429	0.92
Mar del Plata *(1975), Pampeana*	1,168	23,335	673	642	2,701	706	963	769	0.92
Misiones *(1973), NEA*	686	20,733	290	457	748	379	327	553	0.89
Nordeste *(1956), NEA*	2,912	50,934	536	199	3,424	623	869	920	0.95
Patagonia Austral *(1994), Patagonia*	119	6,959	158	293	491	224	203	297	0.77
Patagonia S. J. Bosco *(1980), Patagonia*	417	13,300	227	566	1,560	472	428	556	0.92
Quilmes *(1989), GBA*	985	15,020	233	116	262	220	136	168	0.67
Rosario *(1968), Pampeana*	5,686	73,227	1,056	2,061	4,991	1,412	1,922	1,230	0.98
Río Cuarto *(1971), Pampeana*	906	16,643	764	576	330	551	584	366	0.87
Salta *(1972), NOA*	468	24,087	429	767	410	388	527	394	0.86
San Juan *(1973), Cuyo*	582	19,458	868	1,038	1,143	1,141	532	493	0.94
San Luis *(1973), Cuyo*	566	12,703	757	444	154	515	502	408	0.93
San Martín *(1992), GBA*	754	10,862	96	225	733	281	111	551	0.84
Santiago del Estero *(1973), NEA*	708	14,001	331	251	203	285	223	181	0.86

[12] The exchange rate was ARS 4.93 = USD 1 in January 2nd, ARS 5.39 in July 1st, and ARS 6.53 in December 30th, 2013. The July 1st is a reasonable mean of the whole year average Price.

University	Graduates	Students	Exclusive	S-exclusive	Simple	Professors_w	Assistants_w	Expenditures	Rprodst
Sur *(1956), Patagonia*	1,032	19,493	614	275	1,334	519	566	387	0.94
Tecnológica Nacional *(1948), Pampeana*	4,071	73,144	542	819	17,216	3,009	2,247	2,520	0.88
Tres de Febrero *(1995), GBA*	237	8,936	90	136	145	157	37	247	0.72
Tucumán *(1912), NOA*	2,096	61,418	1,315	2,191	691	1,254	1,329	1,010	0.97
Villa María *(1996), Pampeana*	152	4,004	114	285	143	135	157	71	0.66
Total	66,371	1,291,169	19,096	28,902	83,273	25,971	28,393	42,633	

Source: Own elaboration on "Anuarios de Estadísticas Universitarias".

TABLE 2

DESCRIPTIVE STATISTICS OF THE WHOLE SAMPLE OVER 2005-2013 (N=333)

Variable	Mean	Std. Dev.	Min	Max
Graduates	1,794	2,996	24	18,124
Students	34,896	54,356	1,111	358,071
Exclusive	516	503	0	2,478
Semi-exclusive	781	796	44	3,589
Simple	2,251	4,176	0	21,214
Professors	1,473	1,992	115	10,522
Assistants	2,075	3,202	2	18,636
Professors_w	702	715	53	3,224
Assistants_w	767	1,046	1	6,011
Expenditures (millions 2013 AR$)	1,140	2,790	3	30,200
GBA	0.243	0.430	0	1
NOA	0.162	0.369	0	1
NEA	0.108	0.311	0	1
Cuyo	0.081	0.273	0	1
Pampeana	0.324	0.469	0	1
Patagonia	0.081	0.273	0	1
Rprodst	0.866	0.148	0.187	1

Source: Own elaboration on "Anuarios de Estadísticas Universitarias".

4. RESULTS

First, to select the model specification for the production function, we estimate four models for the whole sample by pooled OLS. We use a linear specification and the nonlinear log-lin, lin-log and log-log (Cobb Douglas) ones. We consider Graduates as the dependent variable while the independent variables included are Students, Professors_w, Assistants_w, Expenditures, the regions GBA, NOA, NEA, Cuyo, Pampeana, the Time Trend and a Constant.

As showed in Table 3, most of the signs of the significant variables are the expected ones and are robust to all specifications. The BIC information criterion favors the log-log specification, then we employ it as our "basis model".

TABLE 3

HIGHER EDUCATION PRODUCTION FUNCTION UNDER ALTERNATIVE SPECIFICATIONS (POLS)

Variables	Model Specification			
	linear	log-lin	lin-log	log-log
Students	0.045***	0.000	1,277.341***	0.844***
	(0.005)	(0.000)	(332.880)	(0.070)
Professors_w	0.378**	0.001***	702.347	0.531***
	(0.152)	(0.000)	(430.467)	(0.101)
Assistants_w	0.156	0.000	155.768	-0.126***
	(0.265)	(0.0005)	(148.810)	(0.043)
Expenditures	0.000	0.000***	472.551***	0.003
	(0.000)	(0.000)	(146.583)	(0.022)
GBA	489.821***	0.790***	2,086.486***	0.7290***
	(83.445)	(0.172)	(491.393)	(0.090)
NOA	-206.889***	-0.078	120.593	-0.147*
	(78.983)	(0.182)	(363.263)	(0.084)
NEA	359.876***	0.995***	396.699	0.622***
	(85.177)	(0.173)	(310.857)	(0.096)
Cuyo	142.673	0.350	-690.903**	0.243**
	(114.559)	(0.214)	(333.124)	(0.117)
Pampeana	428.535***	0.649***	329.813	0.595***
	(68.716)	(0.155)	(292.896)	(0.066)
Trend	4.725	0.034**	-140.499***	0.003
	(15.366)	(0.017)	(54.065)	(0.009)
Constant	-480.780***	5.081***	25,410.432***	-4.667***
	(96.495)	(0.174)	(2,930.968)	(0.338)
Observations	323	323	323	323
R-squared	0.962	0.704	0.678	0.927
BIC	5103.149	5191.901	5792.577	4746.398

Source: Own elaboration.
Note: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1
Before performing the SFA models, we test the residuals of the chosen Cobb Douglas POLS model to check for the validity of the stochastic frontier method. The idea behind the test is that for the production frontier model (with a composed error $v_{it} - u_{it}$, $u_{it} \geq 0$ and v_{it} distributed symmetrically around zero), the residuals of the corresponding OLS estimation should skew to the left. The calculated statistic for the skewness is equal to -0.475, and it is statistically significant (p-value=0.001) indicating that the distribution of the residuals, skews to the left (see Figure 1).[13]

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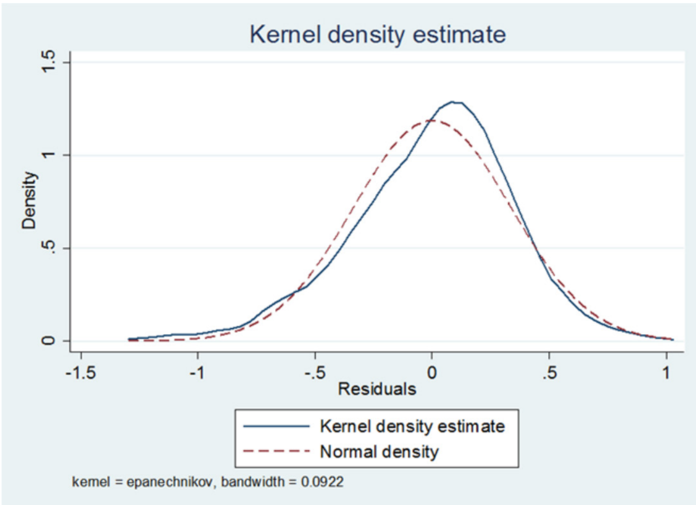
[13] The statistic test performed is that proposed by Schmidt and Lin (1984) and is defined as: $b_1^{1/2} = \dfrac{m_3}{m_2\, m_2^{1/2}}$, where m_2 and m_3 are the second and third sample moment of the OLS residuals, respectively.

FIGURE 1

DISTRIBUTION OF OLS RESIDUALS (LOG-LOG POLS MODEL)



As the residuals of the sample have the correct characteristic for the implementation of the procedure of maximum likelihood, we next estimate the SF models using the chosen Cobb Douglas (double log) form for the production function. For observed heterogeneity, we use the ratio number of students of university *i* in period *t* divided on the maximum number of students of university *i* over the period 2005-2013 ($rprodst_{it}$) as a measure of enrollment efficiency.

As can be seen in Table 4, in terms of signs and significance, results almost do not differ among specifications, except in the case of the TFE model where none of the regional dummy is statistically significant. All the significant coefficients have the expected sign and have similar magnitudes among models. The number of students has a positive effect on the determination of the stochastic production frontier, but the teachers' effects differ: the number of professors has a positive impact while the effect is negative when assistant professors are considered. This could be explained because the proportion of assistants is customarily larger in the initial years of the different programs, where the courses are more general, than in the following years, and the drop-out rates are there also the largest.

Only in the RE model the university expenditure explains the production of graduates. Then, it seems that human resources are more important for the definition of the production frontier than the budget allocated to each university. Regarding the regional variables all the models except TFE show that the geographical region explains the number of graduates. Ceteris paribus, all universities have a positive significant differential in the number of graduates regarding the basis region (Patagonia). The time variable is in general positive, but it is never statistically significant, meaning that there is not any technological development over the period under analysis.

As it is shown in Table 4, the enrollment efficiency measure (rprodst) has the expected negative sign, but it is not significant for explaining the distribution of the mean of inefficiency in the RE model, however it is significant in the model that considers both observed and unobserved heterogeneity (TRE+REH). The estimated inefficiency variance is significant in all models, while it presents the highest value in the RE one. This means that some of the inefficiency captured in the RE model is in fact heterogeneity. Finally, the parameter θ, which characterizes the simulated standard distribution of the university specific intercept term (w_i), is statistically significant indicating the presence of heterogeneity among universities.

TABLE 4
ESTIMATION RESULTS OF THE ALTERNATIVE SFA MODELS

Variables	Alternative models				
	RE	REH	TFE	TRE	TRE+REH
ln Students	0.772*** (0.076)	0.888*** (0.062)	0.889*** (0.104)	0.865*** (0.067)	0.854*** (0.066)
ln Professors_w	0.602*** (0.107)	0.500*** (0.093)	0.507*** (0.128)	0.276*** (0.095)	0.283*** (0.092)
ln Assistants_w	–0.158*** (0.041)	0.158*** (0.034)	0.151*** (0.046)	–0.085** (0.036)	–0.088** (0.037)
ln Expenditures	0.037* (0.020)	–0.007 (0.024)	–0.001 (0.019)	0.023 (0.017)	0.023 (0.017)
GBA	0.823*** (0.140)	0.724*** (0.083)	0.917 (0.989)	0.649*** (0.146)	0.658*** (0.146)
NOA	–0.177 (0.139)	–0.147** (0.075)	–0.243 (0.857)	–0.140 (0.148)	–0.139 (0.149)
NEA	0.660*** (0.154)	0.607*** (0.088)	0.887 (1.037)	0.671*** (0.160)	0.679*** (0.155)
Cuyo	0.369** (0.162)	0.372*** (0.096)	0.454 (1.036)	0.323** (0.159)	0.321** (0.158)
Pampeana	0.573*** (0.130)	0.544*** (0.068)	0.623 (1.243)	0.550*** (0.139)	0.553*** (0.138)
Trend	–0.004 (0.007)	0.003 (0.009)	0.007 (0.007)	0.006 (0.006)	0.004 (0.005)
Constant	–4.566*** (0.520)	4.238*** (0.360)		–3.748*** (0.418)	–3.666*** (0.397)
Observations Number of groups	323 37	323 37	323 37	323 37	323 37
Log-likelihood BIC	–38.382 151.873	–95.062 276.789	44.727 164.763	–17.336 121.336	–15.724 118.113

Variables	Alternative models				
	RE	REH	TFE	TRE	TRE+REH
Mu					
Rprodst		–1.581 (2.627)			170.148*** (0.759)
Constant		–1.129 (3.100)		302.097*** (10.262)	–106.005
sigma_u					
Constant	0.405*** (0.060)	0.941 (0.701)	0.213*** (.0203)	8.071*** (0.431)	7.362*** (0.014)
sigma_v					
Constant	0.241*** (0.010)	0.206*** (0.023)	0.106*** (0.015)	0.114*** (0.016)	0.112*** (0.012)
Theta				0.262*** (0.036)	0.262*** (0.035)

Source: Own elaboration.
Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Regarding the efficiency scores estimated with the alternative SFA models (see Table 5), the mean efficiency over the entire period goes from 75 percent to 82 percent depending on the model considered. This means that from 18 percent to 25 percent of the production (graduates) is lost due to inefficiency. These values are in line with previous non-parametric studies in Argentina (inefficiency from 23.2 percent to 23.9 percent in Coria, 2011, and average efficiency of 78.6 percent in Quiroga Martínez, Fernández-Vázquez and Alberto, 2018). Besides, as expected, those models that account for unobserved heterogeneity present higher values of TE while the RE model presents the lowest value. This result indicates that there is evidence of heterogeneity that overestimates inefficiency.

TABLE 5

DESCRIPTIVE STATISTICS OF THE ESTIMATED EFFICIENCY SCORES (JLMS TECHNIQUE)

Variable	Mean	Std. Dev.	Min	Max
RE	0.749	0.152	0.371	0.951
REH	0.764	0.143	0.259	0.951
TFE	0.825	0.141	0.237	0.972
TRE	0.816	0.141	0.238	0.967
TRE+REH	0.821	0.137	0.237	0.969

Source: Own elaboration.

Table 6 presents a correlation among the estimated inefficiency scores of the alternative models. As can be observed, the ranks of the RE model are highly correlated with those of the REH model, weakly correlated with the ranks of the TRE+REH specification, and not statistically correlated with the ranks of the TFE and TRE models. This means that the ranking of the technical efficiency scores differs depending on the model chosen, more specifically it depends whereas the model accounts for unobserved university-specific differences. In fact, the RE and the REH model rank the universities similarly, while the rankings of the TFE and the TRE models are highly correlated.

TABLE 6

CORRELATION OF INEFFICIENCY ESTIMATE

	RE	REH	TFE	TRE	TRE+REH
RE	1				
REH	0.721	1			
	0.000				
TFE	0.074	0.657	1		
	0.184	0.000			
TRE	0.082	0.657	0.984	1	
	0.141	0.000	0.000		
TRE+REH	0.137	0.703	0.989	0.987	1
	0.014	0.000	0.000	0.000	

Source: Own elaboration.
Note: p-value in italics.

In Table 7 we present the ranking of the public universities according to their estimated efficiency score. As expected, the ranking is similar among the TFE, the TRE and the TRE+REH models. When analyzing university by university, in these latter models the ranks of the Universities of Rosario, Entre Ríos and Lomas de Zamora decrease compared with the RE and REH rankings, while the positions of other big Universities such as the Universities of Córdoba, La Plata and Buenos Aires increase. This result indicates that there are heterogeneity factors that influence inefficiency.[14]

[14] We can advance one possible explanation since the proportion of working students varies among the universities of the sample. Using the data of the *Household Survey of INDEC* (EPH) for the period under analysis we find that those universities which substantially improve their performance are those located in urban agglomerates which present the highest rates of working students.

TABLE 7

TECHNICAL EFFICIENCY (TE) SCORES BY UNIVERSITY (AVERAGE 2005-2013)

University	RE TE score	University	REH TE score	University	TFE TE score	University	TRE TE score	University	TRE+REH TE score
Lomas de Zamora	0.9514	Cuyo	0.9028	Córdoba	0.8906	Cuyo	0.8916	Cuyo	0.8973
Rosario	0.9442	Lomas de Zamora	0.8990	Cuyo	0.8898	Nordeste	0.8858	Nordeste	0.8901
Cuyo	0.9324	Rosario	0.8958	Sur	0.8896	Córdoba	0.8836	Córdoba	0.8884
Entre Ríos	0.9311	Nordeste	0.8873	Tecnológica Nacional	0.8894	Sur	0.8830	Sur	0.8863
Tucumán	0.9285	Tucumán	0.8872	Buenos Aires	0.8887	La Plata	0.8789	Mar del Plata	0.8814
Nordeste	0.9284	Entre Ríos	0.8748	Mar del Plata	0.8879	Mar del Plata	0.8780	La Plata	0.8809
Comahue	0.9232	Córdoba	0.8722	Misiones	0.8847	Buenos Aires	0.8750	Buenos Aires	0.8801
Quilmes	0.9168	Comahue	0.8570	La Plata	0.8845	Tucumán	0.8740	Tecnológica Nacional	0.8795
La Rioja	0.8856	San Martín	0.8470	Litoral	0.8843	Tecnológica Nacional	0.8735	Tucumán	0.8791
San Martín	0.8486	Sur	0.8346	Nordeste	0.8822	Patagonia San Juan Bosco	0.8720	Patagonia San Juan Bosco	0.8754
Sur	0.8449	Luján	0.8276	Patagonia San Juan Bosco	0.8813	Litoral	0.8697	Litoral	0.8709
Catamarca	0.8329	Río Cuarto	0.8242	La Pampa	0.8751	Río Cuarto	0.8694	Río Cuarto	0.8705
San Luis	0.8319	Catamarca	0.8165	Río Cuarto	0.8744	Luján	0.8655	Luján	0.8701
Río Cuarto	0.8298	Patagonia San Juan Bosco	0.8130	Luján	0.8720	Misiones	0.8645	La Pampa	0.8669
Villa María	0.8297	Buenos Aires	0.8116	Tucumán	0.8716	San Martín	0.8621	Misiones	0.8664
Patagonia San Juan Bosco	0.8143	Mar del Plata	0.8086	San Juan	0.8712	La Pampa	0.8620	San Martín	0.8608
Santiago del Estero	0.8053	La Plata	0.8052	Centro de la PBA	0.8634	Lomas de Zamora	0.8550	Lomas de Zamora	0.8603

University	RE TE score	University	REH TE score	University	TFE TE score	University	TRE TE score	University	TRE+REH TE score
Luján	0.7952	Quilmes	0.8032	Villa María	0.8619	Centro de la PBA	0.8530	San Luis	0.8573
Córdoba	0.7727	La Rioja	0.7991	San Martín	0.8518	San Luis	0.8519	Centro de la PBA	0.8537
La Pampa	0.7459	San Luis	0.7916	San Luis	0.8513	Lanús	0.8509	Lanús	0.8495
Salta	0.7408	La Pampa	0.7718	Catamarca	0.8474	Villa María	0.8482	Catamarca	0.8478
Mar del Plata	0.7402	Santiago del Estero	0.7701	Lanús	0.8462	Catamarca	0.8442	San Juan	0.8392
Formosa	0.7108	Litoral	0.7504	Lomas de Zamora	0.8298	San Juan	0.8350	Villa María	0.8373
Tecnológica Nacional	0.6981	Centro de la PBA	0.7501	Entre Ríos	0.8276	Comahue	0.8238	Comahue	0.8253
Lanús	0.6917	Tecnológica Nacional	0.7389	Comahue	0.8201	Entre Ríos	0.8229	Entre Ríos	0.8216
Chilecito	0.6820	Villa María	0.7327	La Rioja	0.8092	La Rioja	0.8167	La Rioja	0.8090
Centro de la PBA	0.6600	Salta	0.7176	Jujuy	0.7946	Santiago del Estero	0.7782	Rosario	0.7762
La Plata	0.6546	La Matanza	0.7170	Patagonia Austral	0.7877	Rosario	0.7724	Santiago del Estero	0.7734
Litoral	0.6538	Formosa	0.7030	Santiago del Estero	0.7864	Jujuy	0.7684	Jujuy	0.7687
La Matanza	0.6346	Lanús	0.6939	Rosario	0.7600	Patagonia Austral	0.7617	Patagonia Austral	0.7557
General Sarmiento	0.6030	General Sarmiento	0.6363	La Matanza	0.7555	La Matanza	0.7560	La Matanza	0.7516
Jujuy	0.5651	Misiones	0.6221	Salta	0.7360	Salta	0.7364	Salta	0.7348
Patagonia Austral	0.5500	Chilecito	0.6194	Tres de Febrero	0.6997	General Sarmiento	0.7097	General Sarmiento	0.6972
Misiones	0.5469	Jujuy	0.5809	General Sarmiento	0.6972	Tres de Febrero	0.7052	Tres de Febrero	0.6961
Buenos Aires	0.5464	Patagonia Austral	0.5590	Quilmes	0.6818	Quilmes	0.7043	Quilmes	0.6956
Tres de Febrero	0.3847	San Juan	0.4570	Chilecito	0.6711	Chilecito	0.6771	Formosa	0.6763
San Juan	0.3707	Tres de Febrero	0.4322	Formosa	0.6625	Formosa	0.6723	Chilecito	0.6594

Source: Own elaboration.

To complete the analysis, we check for the robustness of our results. To doing so, we first choose one of the five alternative fixed/random effects SFA models (i.e. RE, REH, TFE, TRE and TRE+REH) using the Hausman test and the BIC criterion. Secondly, with the model chosen in the previous step, we perform the sensitivity analysis. The Hausman test compares the fixed effect estimator that is known to be consistent, with the random effects estimator that is efficient under the assumption being tested.[15] The statistic is distributed as χ^2 and the null hypothesis is that the random effect estimator is indeed an efficient (and consistent) estimator of the true parameters. In our case, the χ^2 statistic is negative when comparing the TFE model with the RE model ((χ^2 *(10)*=-23.03), with the TRE model (χ^2 *(9)*=-89.17) and with the TRE+ REH one (χ^2 *(10)*=-33.78). This result might be interpreted as strong evidence that we cannot reject the null hypothesis and that random effects might be appropriate for modeling the SF (Stata, 2019 p. 899). When comparing the TFE model with the REH one, the χ^2 (10)=4.89 and, therefore, we cannot reject the null hypothesis that the random model is the more appropriate. Then, among the random effects models TRE+REH specification was selected since it shows the lowest BIC value.

For the sensitivity analysis, we first separate the total expenditure into its components (i.e. personnel, consumption, goods and services and transfers). Since almost 90 percent of these expenditures are due to salaries, this type of expenditure could be reflected in the teaching variables. Then model S1 includes all the expenditures' components except those that refer to personnel.

In model S2 we tested the role of research in the production frontier. Unfortunately, the database does not include any account for publications, patents, or other quantifiable research outputs, neither does it include mention to grants or other financial resources devoted to those activities. The quantifiable variable that we include is the percentage of faculty of national universities under the program of research incentives.[16] This program was introduced in the early 1990s as a sort of supplemental compensation for public universities' faculty included in accredited research projects. The incentive program categorizes the faculty in five types of researchers. Quiroga-Martinez, Fernández-Vázquez and Alberto. (2018) chose to assign weights to the categories and to disaggregate them in two broad groups. For simplicity, we considerate all incentivized faculty in one variable. Per university, we calculate the percentage of professors and teaching assistants under the program over total faculty in each institution.

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[15] For details about this test, see Hausman (1978).

[16] The "Program of Incentives to Research in National Universities" works as a supplement on salaries of professors and teaching assistants of public Argentine universities. Candidates should apply first for a qualitative category (A, B, C, etc.) which is assigned on basis of the professorship category and research individual outcomes. The categorized educator has then to apply as a member of a project crew and claim the benefit. It is not paid synchronically with salaries. Instead, it is paid quarterly and frequently with one or two quarters of delay.

In the next two models, we use two alternative specifications to measure the teachers' effects. In model S3, we consider the teachers according to their role (professor or assistant) and we include an environmental variable defined as $exclusive\_p = \dfrac{exclusive}{(exclusive + 0.5\ semi + 0.25\ simple)}$ to take into account the proportion of full-time over total full-time equivalent faculty.

In model S4, we consider the number of professors according to their time dedication (exclusive, semi-exclusive or simple). This classification comprised every existing category in the national system, going from full-time professors holding a permanent chair, and from full- and part-time assistants. We also include an environmental variable defined as $professors_p = \dfrac{professor}{(professor + assistant)}$ to account for the proportion of professors in the regression.

Finally, in all models we include an alternative measure of enrollment efficiency in the efficiency equation (*rprodnst*) defined as the ratio number of enrollees of university *i* in period *t* divided on the maximum number of enrollees of university *i* over the period 2005-2013 (model S5).

Table 8 presents the different sensitivity models. As can be seen, the results are in line with those of the basis TRE-REH model (see Table 4). In all the specifications, the number of students has a positive and significant effect on the graduates while the teachers' effects differ depending on their role (professors show positive impact while assistants have a negative sign). When the incentives for researching are included (model S2), the variable shows a positive sign. However, it is not statistically significant for explaining the number of graduates.

An interesting finding is that, when considering total expenditures as a whole this variable is never statistically significant. However, when their different components (those different from the personnel expenditures) are explicitly accounted for, the consumption expenditure variable shows a statistically significant positive sign. This result indicates that the expenditure made on materials and supplies for the operation of the universities has a positive effect on the number of graduates. Finally, the geographical regions explain the number of graduates as in the previous basis TRE-REH model.

TABLE 8

SENSITIVITY ANALYSIS: ALTERNATIVE SPECIFICATIONS OF THE TRE-REH MODEL

Variables	S1	S2	S3	S4	S5
ln Students	0.874***	0.852***	0.891***	0.897***	0.863***
	(0.076)	(0.069)	(0.062)	(0.118)	(0.067)
ln Professors_w	0.330***	0.282***			0.274***
	(0.103)	(0.095)			(0.095)
ln Assistants_w	–0.095***	–0.088**			–0.085**
	(0.038)	(0.037)			(0.036)
Incentives		0.001			
		(0.011)			
ln Consumption	0.077**				
	(0.042)				
ln Services	–0.081				
	(0.050)				
ln Goods	–0.012				
	(0.021)				
ln Professor			0.228***		
			(0.080)		
ln Assistants			–0.095***		
			(0.036)		
ln Exclusive_p			–0.018		
			(0.046)		
ln Expenditures		0.023	0.022	0.016	0.023
		(0.017)	(0.016)	(0.012)	(0.017)
ln Exclusive				0.015	
				(0.122)	
ln Semi Exclusive				0.001	
				(0.062)	
ln Simple				0.044	
				(0.038)	
ln Professors_p				0.143	
				(0.132)	
GBA	0.749***	0.656***	0.582***	0.765*	0.650***
	(0.163)	(0.147)	(0.209)	(0.395)	(0.146)
NOA	–0.150	–0.141	–0.139	–0.103	–0.143
	(0.156)	(0.149)	(0.202)	(0.217)	(0.148)
NEA	0.583***	0.681***	0.626***	0.530	0.671***
	(0.221)	(0.155)	(0.213)	(0.351)	(0.159)
Cuyo	0.384***	0.319**	0.617**	0.597**	0.323**
	(0.174)	(0.159)	(0.255)	(0.290)	(0.159)
Pampeana	0.519***	0.552***	0.558***	0.673**	0.548***
	(0.153)	(0.139)	(0.198)	(0.313)	(0.139)
Trend	0.015***	0.004	0.005	0.007	0.005
	(0.011)	(0.006)	(0.005)	(0.009)	(0.006)
rprodst	–115.056***		171.399***	–114.876	
	(11.835)		(1.266)	(200.962)	
rprodnst					–68.068***
					(10.348)

Variables	S1	S2	S3	S4	S5
Constant	–3.309*** (0.518)	3.638*** (0.474)	–3.712*** (0.384)	–3.077 (0.000)	–3.715*** (0.407)
Observations Number of id	323 37	323 37	322 37	311 36	323 37
Log-likelihood BIC	–14.701 133.4117	–15.718 129.656	–14.637 127.442	–7.9163 107.669	–17.130 126.702

Source: Own elaboration.

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Moreover, the TE scores obtained are highly and positively correlated with those of the basis TRE-REH model (the correlation coefficients undertake values over 95 percent among specifications). This indicates that the estimated TE in the base TRE-REH regression is robust to the alternative specifications performed in the sensitivity analysis.

5. SUMMARY AND CONCLUSIONS

This paper estimates the technical efficiency in teaching activity in Argentine public universities using SFA. We compare conventional models that do not account for heterogeneity with heterogeneity-extended SFA models.

We applied the basic “random effect model”, an extension of the “random effect model that includes observed heterogeneity” to the mean of the inefficiency distribution, a “true fixed effects model” and a “true random effects model” (both accounting for unobserved heterogeneity), and a combination of the “true random effect model” with the extended random effect model.

We work with data from the Ministry of Education of Argentina. Our dataset consists of a balanced panel of 37 National Universities in Argentina with information over the period 2005-2013. We find that, in terms of signs and significance, results almost do not differ among specifications, except in the case of the TFE model where none of the regional dummy is statistically significant (however, the majority of the specific dummy variables are significant).

All the significant coefficients have the expected signs and have similar magnitudes across the models. The number of students has a positive effect on the determination of the production frontier, but the teachers’ effects differ by roles: the number of professors has a positive impact, while the effect is negative when assistant professors are considered. This is coherent with the observed practice of having a larger proportion of assistants working in the initial years in basic (general) courses, where drop-out rates are the largest.

Only in the RE model, the expenditures explain the production of graduates. Then, it seems that human resources are more important for the definition of the production frontier than the budget allocated to each university. This result is in line with that of the non-parametric study of Quiroga-Martinez, Fernández-Vázquez and Alberto (2018).

Only when the different components of total expenditure are considered separately, the expenditure made on materials and supplies for the operation of the universities shows a significant positive effect on the number of graduates. Regarding the regional variables, all the models show that the geographical region explains the number of graduates. Ceteris paribus, all universities have a positive significant differential in the number of graduates regarding the baseline region (Patagonia) with the exception of those located in the north-west part of the country (NOA).

The time-trend variable is in general positive, but it is never statistically significant, meaning that there is no technological progress over the period under analysis. In the same vein, the faculty incentives variable does not appear significant in the estimates.

Regarding the estimated efficiency scores, the mean efficiency over the entire period goes from 75 to 82 percent depending on the model considered. This means that from 18 to 25 percent of the production (graduates) is lost due to inefficiency. These values are similar to those found in previous studies for Argentina (Alberto, Carignano and Ercole, 2010; Coria, 2011; Quiroga-Martinez, Fernández-Vázquez and Alberto, 2018) and are also in line with the international experience, which find values of average efficiency around 80 percent (Johnes, 2006). Besides, as expected, those models that account for unobserved heterogeneity present higher values of TE while the RE model presents the lowest value. This result indicates that there is evidence of heterogeneity, and that not paying attention to this fact overestimates inefficiency. Our results are robust to different model specifications.

This study adds insight into the estimation of technical efficiency in Latin American universities. However, some limitations remain. One is the difficulty in identifying the "capital intensity" required by the different fields in each university. This information could provide more robust results. Unfortunately, our sources do not include this information. Another drawback is the lack of a better measure of research activity. Once again, the database does not include any statistics regarding publications, patents, or other quantifiable research outputs. Finally, as in all previous empirical articles on this issue, externalities are not either considered in this study due to the lack of information. In this sense, this paper could be an opportunity for the policy makers to improve the existing databases.

Although it is beyond the objective of the paper to conclude any meaningful policy recommendation, we would like to highlight some points. First, this kind of analysis calls for caution regarding measures to improve graduation results such as quality-insensitive cost cutting, relaxing effort demanded on students, and focusing only on administrative efficiency (Gates and Stone, 1997 characterize some policy suggestions). Second, higher education is a knowledge intensive industry, it requires high-quality human resources and financial resources, but if incentives are not set properly (clear aims and goals in terms of outputs), money could be spent inefficiently. Third, every effort in adequately address quality and environmental issues enriches the decision making.

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