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Essays on the Efficiency of Higher Education

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Abstract

The European Higher Education (HE) sectors have recently undergone significant structural transformations. First, an extensive reform process aimed at improving institutional performance and aligning European systems has mandated universities to enhance their efficiency. In addition, the COVID-19 pandemic crisis fits into this context, forcing universities to reorganize their teaching and research activities. The thesis analyses the efficiency of HE institutions in response to structural changes in the sector, shedding light on the primary changes and policy levers that have influenced institutional performance.

The first chapter of the thesis examines efficiency trends in Italian public universities from 2010 to 2019. In the first half of this timeframe, the Italian HE system underwent substantial reforms to deregulate universities and enhance efficiency by modifying the governance and funding system. We employ an innovative approach to decompose overall inefficiency into two terms: persistent (structural) and transient (institutional) inefficiency. The results show considerable heterogeneity in the overall inefficiency of universities. Although inefficiency decreased across all regions over time, this improvement primarily resulted from enhancements in transient efficiency, while persistent inefficiency significantly contributes to inefficiency in certain areas. The findings reveal that underperforming universities partially bridged the gap with their better-performing counterparts. Lastly, the analysis suggests that regional GDP does not significantly impact inefficiency levels, whereas inefficiency tends to rise with increasing unemployment rates. The study presents important implications for regional policies, highlighting the need to consider local economic conditions.

The second chapter explores the impacts of increased public support for Italian universities during and after the COVID-19 pandemic. In response to the pandemic the Italian government has increased its financial backing for universities. While this surge in financial resources may partially alleviate some adverse effects of the pandemic on outputs, it also substantially raises inputs and costs for universities, potentially resulting in a temporary decline in efficiency. We examine the influence of increased funding on the efficiency of universities in Italy, focusing on production and cost efficiency. By employing a panel dataset covering five years (2017–2021) and utilizing the recently developed Generalized True Random Effect stochastic frontier model, we are able to decompose the overall inefficiency into persistent and transient components while accounting for university heterogeneity. Our findings indicate that while production efficiency has remained relatively stable over the years, the post-COVID-19 period is characterized by a statistically significant decrease in cost efficiency. This outcome suggests a reversal of the positive efficiency trend observed in Italian universities in recent years. Additionally, we observe a consistent reduction in cost efficiency across geographic regions, indicating that the adverse effect is not linked to specific initial conditions or short-term management decisions.

The third chapter extends its focus to a multinational examination of public universities. The study is grounded in a sample comprising 239 public universities from 10 European countries between 2011 and 2019. Utilizing a four-component stochastic frontier model, we disentangle efficiency into persistent (long-run) and transient (short-run) components, investigating the impact of funding allocation mechanisms on universities' performance. The findings uncover substantial heterogeneity in efficiency scores both across and within countries. Discrepancies among nations seem to be predominantly influenced by long-term inefficiency, underscoring the significance of structural factors in elucidating performance variations within the sector. Further, a high share of tuition fees and third-party funding correlates with better performance. The results highlight the central role of national authorities and governments in shaping the regulatory environment and financial incentives.

The thesis offers valuable insights into the multifaceted nature of efficiency within HE, providing policymakers and stakeholders with empirical evidence to inform strategic decision-making and policy formulation in the pursuit of improved educational outcomes.

Sommario

Il settore dell'istruzione superiore in Europa ha subito significativi cambiamenti strutturali negli ultimi anni. In primo luogo, un ampio processo riformatore volto a migliorare le prestazioni istituzionali e ad allineare i sistemi europei, ha imposto alle università di migliorare la propria efficienza. In questo contesto si è inserita la crisi pandemica da COVID-19, che ha costretto le università a riorganizzare le proprie attività didattiche e di ricerca. La tesi analizza l'efficienza degli istituti d'istruzione superiore in risposta ai cambiamenti strutturali nel settore, facendo luce sulle principali trasformazioni e leve politiche che hanno influenzato le prestazioni istituzionali.

Il primo capitolo della tesi esamina i trend di efficienza delle università pubbliche italiane per il periodo 2010 - 2019. Durante la prima metà di questo periodo, il sistema di istruzione superiore italiano è stato sottoposto a una serie di riforme sostanziali mirate al miglioramento dell'efficienza istituzionale, attraverso modifiche al sistema di governance e di finanziamento delle università. Scomponendo l'inefficienza complessiva in due componenti - inefficienza strutturale persistente e inefficienza istituzionale transitoria - osserviamo una diminuzione dell'inefficienza in tutte le regioni nel corso del tempo. Tuttavia, questo miglioramento è attribuibile principalmente a miglioramenti nell'efficienza istituzionale, mentre l'inefficienza strutturale continua a contribuire in modo significativo all'inefficienza totale in alcune aree del territorio. Inoltre, sebbene esista una certa eterogeneità nei risultati di efficienza tra le università, i risultati rivelano che gli istituti meno performanti sono riusciti a ridurre il divario rispetto alle loro controparti più efficienti. Infine, l'analisi suggerisce che il PIL regionale non ha un impatto significativo sui livelli di inefficienza, mentre l'inefficienza tende a crescere con l'aumento del tasso di disoccupazione. Lo studio presenta importanti implicazioni per le politiche regionali, sottolineando la necessità di tenere conto delle condizioni economiche locali.

Il secondo capitolo esplora l'impatto dell'aumento del sostegno pubblico alle università italiane durante e dopo la pandemia COVID-19. In risposta alla pandemia, il governo italiano ha aumentato il sostegno finanziario alle università. Sebbene sia ragionevole aspettarsi che l'afflusso di risorse finanziarie possa in parte mitigare gli effetti negativi della pandemia sugli output, contemporaneamente l'aumento dei costi per le università potrebbe portare a una temporanea diminuzione dell'efficienza. Utilizzando dati panel per il periodo 2017-2021 e facendo uso del modello di frontiera stocastica Generalized True

Random Effect (recentemente sviluppato), scomponiamo l'inefficienza complessiva in due componenti (persistente e transitoria), tenendo conto dell'eterogeneità delle università. I nostri risultati indicano che, mentre l'efficienza di produzione è rimasta relativamente stabile nel corso degli anni, il periodo post-COVID-19 è caratterizzato da una diminuzione statisticamente significativa dell'efficienza dei costi. Questo risultato indica un'inversione di tendenza rispetto all'aumento della performance osservato nelle università italiane negli ultimi anni. Inoltre, la riduzione dell'efficienza è omogenea tra le aree geografiche, indicando che l'effetto negativo non è legato a specifiche condizioni iniziali o a decisioni gestionali di breve periodo.

Il terzo capitolo estende il focus a un'analisi sovranazionale delle università pubbliche, basata su un campione di 239 istituzioni in 10 paesi europei nel periodo compreso tra il 2011 e il 2019. Utilizzando un modello di frontiera stocastica a quattro componenti, si scompone l'efficienza in una componente persistente (di lungo periodo) e transitoria (di breve periodo), indagando sull'impatto dei meccanismi di allocazione dei finanziamenti sulle prestazioni delle università. I risultati rivelano una considerevole eterogeneità nei punteggi di efficienza sia tra che all'interno dei paesi. Le discrepanze tra i paesi sembrano essere influenzate principalmente dall'inefficienza di lungo periodo, sottolineando l'importanza dei fattori strutturali nello spiegare le variazioni di efficienza all'interno del settore. Inoltre, una quota elevata delle tasse universitarie e dei finanziamenti da parte di terzi correla positivamente con migliori performance. I risultati evidenziano il ruolo centrale delle autorità nazionali e dei governi nel disegnare un quadro regolatorio e degli incentivi finanziari favorevoli.

La tesi fornisce preziose intuizioni sulla complessa natura dell'efficienza nell'istruzione superiore, offrendo agli attori politici e agli stakeholder evidenze empiriche per informare la formulazione di decisioni strategiche e politiche volte a migliorare i risultati del settore.

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Chapter 1

Deregulation, efficiency and catch-up of Italian public universities*

with Oleg Badunenko[1]

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Abstract

We study the efficiency patterns of Italian public universities from 2010 to 2019. During the first half of this period, the Italian Higher Education system underwent significant reforms to deregulate universities and improve efficiency by changing the governance and funding system. We use a novel approach to break down overall efficiency into two components: persistent structural efficiency and transient institutional inefficiency. We find relevant heterogeneity in overall efficiency among universities. Although inefficiency decreased across all regions over time, this improvement was primarily due to enhancements in transient efficiency, while persistent inefficiency remained a significant contributor to inefficiency in certain areas. Our findings show that poorly performing universities were able to catch-up by narrowing the gap with their better-performing counterparts. Finally, our analysis indicates that regional GDP does not significantly affect inefficiency levels, while inefficiency tends to increase with rising unemployment rates. As such, our study has important implications for regional policies, highlighting the need to consider local economic conditions.

1.1 Introduction

There is widespread consensus on the positive role that Higher Education (HE) institutions play in fostering regional economic development (Cuaresma et al.; 2014; Bramwell and Wolfe; 2008; Janzen et al.; 2022). Universities promote human capital development and knowledge creation strengthening regional competitiveness (Gumbau-Albert and Maudos; 2009; Barrio-Castro and García-Quevedo; 2005; Drucker; 2016). Efficient and high-quality universities are thus essential for local and global development. The

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literature shows that the efficiency of universities is directly related to the economic development of the regions in which they operate (Agasisti et al.; 2019), making the measurement of efficiency essential for understanding regional disparities and designing effective public policies. In this regard, the regional gaps in economic development and labor market conditions that characterize the Italian context are a subject of concern. The per capita GDP of the southern regions is systematically lower than that of the other regions of Italy. The latest regional economic statistics indicate that in 2021 the Northwest has the highest per capita GDP (37.5 thousand), followed by the Northeast (35.8 thousand) and the Center (32.1 thousand), with the South and Islands having the lowest GDP (19.7 thousand euro) (ISTAT; 2021). The labor market exhibits differences of the same magnitude: between 2000 and 2020, although employment increased at the national level (+6.1%), the growth in the Center-North regions (+9.8%) was offset by a fall in the southern areas (-3.2%), extending the already existing disparity (SVIMEZ; 2021).

The interregional differences are also noticeable in the performance of the HE system. Although some historical problems of Italian universities concern the whole system, the literature shows that within the system there is considerable heterogeneity. Universities in the South tend to have lower perceived service quality and research outcomes (De Angelis et al.; 2017). Further, the efficiency gaps between southern and northern universities are particularly severe (Agasisti and Dal Bianco; 2006; Laureti et al.; 2014; Barra et al.; 2018).

To address these issues, a long season of reforms culminating in Law 240/210 (known as the *"Gelmini Reform"*, named after the then Minister of University and Research) has profoundly transformed the Italian HE system (Capano; 2011) by introducing performance-based funding mechanisms and modernizing the governance system. The Gelmini reform sought to improve the quality and efficiency of Italian universities by requiring universities to be more responsible in their use of public funds. In this regard, the reform introduced a performance-based funding system to nudge universities to compete for public funding to incentivize more efficient use of resources and push southern universities towards convergence.

The literature on the effects of the reform is limited and controversial. On the one hand, positive trends have emerged in recent years, such as the general improvement in learning outcomes and the convergence of research results (Abramo and D'Angelo; 2021; Checchi et al.; 2020). On the other hand, the new regulatory framework has been strongly criticized for its architecture, which limits rather than enhances university autonomy (Donina et al.; 2015). It is also important to emphasize that the reform occurred during a period of general austerity, resulting in significant reductions in public funding for tertiary education (Capano; 2010). The new funding system and cuts in public spending have been the subject of concerns about possible imbalance effects among universities (Civera et al.; 2021). Northern universities receive more resources than those in the rest of the country as the funding system tends to penalize institutions in low-income areas (Mariani and Torrini; 2022). Aside from performance-related reasons, external factors beyond the control of university managers may influence this outcome. These factors have fueled the debate on the reform's potential effects on reducing inefficiencies and territorial imbalances. However, as most research employs datasets with a short observation time, no study has shown how university efficiency has changed after reform has been implemented. Consequently, it is unclear how well the new regulatory structure is working to encourage the responsible use of public funding and incentivize the catch-up of underperforming universities.

The primary goal of this paper is to fill this gap by providing evidence on the evolution of efficiency over time (2010-2019) and investigating the degree of convergence of geographical areas. We do so by applying the recently developed four-component Stochastic Frontier (SF) model, the advantage of which lies in the possibility of addressing a previously neglected issue in the analysis of university efficiency, i.e., the sources and the characteristics of inefficiency. Traditionally, efficiency is regarded as the ability to produce the maximum number of output(s) given the level of input(s) available. So far, the literature focuses on the determinants of inefficiency with the idea that university management can implement strategies to gain efficiency (Witte and López-Torres; 2017). Inefficiency, however, is caused not only by management issues but also by long-term structural factors that create unequal initial conditions thereby placing universities in inefficient positions from the outset. We argue that distinguishing between different types of inefficiency is essential to identify efficiency differences within a HE system, as the inefficiencies nature implies a highly differentiated policy response. In this light, our approach allows us to decompose overall inefficiency into a persistent (long-term) and a transient (short-term) component while accounting for institutional heterogeneity. The transitory component is also known as *"Institutional inefficiency"*, which refers to an annual deficit that university managers could eliminate without structural changes (Agasisti and Gralka; 2019). The persistent component, on the other hand, can be interpreted as *"Structural inefficiency"*, as it measures universities' structural or long-term inability to achieve the potential outcomes caused by the HE system as a whole and the university's initial condition.

Secondly, given the relevance of Italian geographic disparities, we examine how local economic conditions influence university production technology and inefficiency. We analyze the factors that explain the inefficiency components (Badunenko and Kumbhakar; 2017). This is the first paper that explores the determinant of persistent and transient inefficiency in the HE literature. In addition to external factors, we investigate the association between institutional settings (such as size, hospital-containing, and multi-site universities) and inefficiency. Our findings show the effectiveness of the new regulatory framework in promoting a virtuous path in the use of public funds, as the overall efficiency increased over the period analyzed. Not shown in the HE literature before and novel to this study, we show that a large portion of overall efficiencies is attributed to structural inefficiency. For this reason, we advocate using the method that takes persistent inefficiency into account to avoid erroneous policy implications and evaluations. Further, our results indicate a catch-up of the poorly performing universities, with institutions in the South and Islands exhibiting the highest efficiency growth rate. Finally, although local economic conditions do not influence production technology, we note that the high regional unemployment rate reduces the efficiency of universities. We advocate a more holistic approach that considers differences in local economic conditions as they affect the efficiency of universities.

The rest of the paper proceeds as follows: after describing and discussing the main changes introduced by the recent reforms in the following section, Section 1.3 reviews the most relevant related literature. Next, Section 1.4 details the methodology applied, while Section 1.5 presents the data and variables used in the analysis. Finally, Section 1.6 summarizes the main findings, and Section 1.8 concludes.

1.2 Background of the regulation

The Italian HE system went through a long reform process that began in the late 1980s and culminated in the Gelmini reform (Law 240/2010). This last reform represented an organic redesign of previous regulatory interventions that, in line with the transformation of higher education systems in many European countries (Capano; 2011), proposed a paradigm shift towards a New Public Management (NPM) perspective. The reform aimed to improve the efficiency and quality of Italian universities by reshaping the governance system, introducing a performance-related funding mechanism, and improving the accountability and evaluation system.

One of the first objectives of the reform was to transform the decision-making process, reducing the power of the Academic Senate in favor of the central governing bodies (Rector and Board of Directors) and simultaneously enhancing the role of stakeholders

(Capano et al.; 2016). The internal structure was also revised, establishing the missions and size of the internal organizational units (Departments), which were given responsibility for planning teaching and research activities.

A further significant change introduced by the reform is the modification of the formula used to allocate the annual lump sum budget (*Fondo di Finanziamento Ordinario, FFO*). The new formula anchors the distribution of public funds to incentive criteria and consists of several parts. The first component is allocated based on the average education costs per student calculated according to the type of degree course and the lower ability to pay tuition fees in low-income areas (*Standard cost per student*). The share to be allocated to each university is determined by multiplying the standard cost per student by the number of students enrolled. However, "non-regular students", i.e. those enrolled beyond the standard course duration, are excluded from the calculation. It follows that this component of the FFO is based on both the demand for education and teaching performance. Therefore, from a quasi-market perspective, this mechanism pushes universities towards competing to increase the number of students in order to attract more public funding while simultaneously trying to reduce the number of non-regular students (Teixeira et al.; 2006). A neglected issue in this incentive scheme concerns the dynamics of Italian student mobility: universities in northern Italy are attended by a high percentage of southern students who emigrate from southern regions to study at universities in the north (ANVUR; 2018). Although the higher attractiveness could be perceived as an indicator of university research and teaching quality (Ciriaci; 2014), the labor market conditions also play a crucial role in explaining student mobility. The Italian students' mobility behavior is strongly affected by the prospects of job vacancies for graduates in the destination regions and by the dynamism of the local labor markets (Dotti et al.; 2013). Moreover, labor market conditions affect the probability of timely completion of studies, which tends to decrease with rising unemployment due to lower opportunity costs of education (Contini et al.; 2018). As a result, the allocation of resources could be affected by factors outside the control of universities, potentially exacerbating regional disparities. The FFO also includes an additional component (*Premium quota*) based on research performance. Italian evaluation agency (*Agenzia Nazionale di Valutazione del Sistema Universitario e della Ricerca*, ANVUR) conducts a research quality assessment (*Valutazione della Qualità della Ricerca*, VQR) according to a peer-review logic. The results of the VQR determine the amount of the premium quota to allocate. In addition, ANVUR evaluates the quality of new academic staff hired by universities, and the results contribute to determining the premium quota.

It is important to emphasize that the Gelmini reform was implemented in the context of significant cuts in public funding. The reduction was 21% between 2009 and 2015 in real terms, with a slight increase in recent years (ANVUR; 2016). The reduction in public funding makes it impossible for universities to fund all costs through FFO, forcing them to rely on tuition fees and external funds (Mariani and Torrini; 2022). Although the tuition fees show limited variation among institutions, there are significant geographic differences, mainly due to the lower ability of students residing in economically disadvantaged regions to contribute (Cattaneo et al.; 2017). In addition, Northern universities attract more funding from other public and private entities than universities in other regions (ANVUR; 2018). Law 240/2010 provided that the standard student cost and the premium quota represent 70% and 30%, respectively. In the current transitional phase, part of the FFO is still allocated based on historical criteria. This tardy implementation is mainly due to the underfunding of the system. The full realization of the reform would lead to the financial collapse of many universities (Mariani and Torrini; 2022). Nevertheless, a considerable amount of funding is allocated on a competitive basis: in 2019, the standard cost covered 23%, and the premium quota was 26.8% of the FFO.

Law 240/2010 has then endowed Italian universities with a quality assurance system called Self-Assessment, Periodic Evaluation, and Accreditation (*Autovalutazione, Valutazione, Accreditamento*, AVA), to ensure that universities operate uniformly and provide an adequate quality of service to their users, to monitor accountability in the use of public resources, and to improve the quality of academic activities (Vinther-Jorgensen et al.; 2019). AVA, in line with the Standards and Guidelines for Quality Assurance in the European Higher Education Area (ESG), provides an evaluation process whereby universities obtain institutional accreditation from the Ministry of Universities and Research. ANVUR, as an external and independent institution, is responsible for periodically assessing the quality of institutions and degree courses offered based on the standards set by the agency itself (Erittu and Turri; 2022).

The new governance system, performance-based funding and evaluation of research and teaching quality introduced by the reform have influenced the activities of universities, likely leading to a change in their ability to produce efficiently. However, the literature has highlighted concerns about the effectiveness of the reform, pointing out contradictions with NPM principles and a funding system that risks exacerbating territorial imbalances.

1.3 Related literature

The literature on the efficiency of HE has increased considerably in recent decades, driven by the demand for better use of public funds (Johnes; 2015; Witte and López-Torres; 2017). Early research focused on the efficiency of departments within single institutions (Johnes and Johnes; 1995; Madden et al.; 1997), however, the vast majority of contributions analyzed differences between universities within the same higher education system with applications in several countries such as the UK (Johnes; 2006), Germany (Gralka; 2018), Spain (Martínez-Campillo and Fernández-Santos; 2020).

The literature on the Italian HE system documents a significant regional gap between universities. Agasisti and Dal Bianco (2009) analyzes teaching efficiency over the period 1999-2004 and finds evidence of an efficiency gap between northern and southern universities, with a small group of efficient universities located mainly in northern regions. Multiple studies corroborate these findings (e.g., Agasisti and Dal Bianco; 2006; Laureti et al.; 2014; Barra et al.; 2018; Agasisti and Pohl; 2012). However, Guccio et al. (2016) show a convergence in the performance of 69 Italian institutions from 2001 to 2011, although the regional gaps remain considerable. Contextually, the evidence reveals a growth in the efficiency of Italian universities over time. Agasisti (2016) shows that the average efficiency of Italian universities between 2001 and 2011 increased observed period, with annual efficiency gains ranging from 1% to about 1.5% based on the specification applied.

Recently, more studies addressed the issue of unobserved heterogeneity, which is particularly relevant in the context of structural socio-economic differentials between regions. Agasisti and Johnes (2010) are the first to exploit the potential of panel data in the Italian context, applying an SF model with institution-specific random parameters (Greene; 2005). In the same vein, Agasisti et al. (2016) estimate the efficiency of the Italian HE system from 2008 to 2011 using a multi-output distance function addressing the incidental parameter problem. They illustrate that ignoring unobservable heterogeneity produces biased estimates. Specifically, they find that the bias is higher for universities operating in southern Italy.

The interpretation of the time-invariant individual component has been at the center of debate in the efficiency literature. Some scholars view it as a time-invariant inefficiency that persists until structural changes occur, such as an ownership or legislative change (e.g., Kumbhakar and Heshmati; 1995). Identifying persistent inefficiency is particularly relevant in the public sector as institutions can more easily survive even if inefficient. On the other hand, other scholars interpret the invariant component as unobservable individual heterogeneity unrelated to inefficiency (e.g., Greene; 2005). The possibility of disentangling persistent inefficiency from unobservable individual heterogeneity has only recently been introduced through the four-component SF model, which allows estimating production technology while decomposing the error into noise, unobservable individual effect, persistent and transient inefficiency (Colombi et al.; 2014). The distinction between transient and persistent components is a new concept in the literature on university efficiency. The transient inefficiency component refers to an annual deficit that university managers could eliminate without structural changes, whereas persistent inefficiency, on the other hand, refers to the structural or long-term inability of universities to achieve potential outcomes (Gralka; 2018; Titus et al.; 2021).

This paper contributes to the existing literature in several ways. Firstly, unlike previous studies, we measure the persistent and transient efficiency of the Italian HE system by exploring regional differences. It appears, only one paper explores the persistent inefficiency in the Italian context (Agasisti and Gralka; 2019). However, the authors compare German and Italian universities over the period 2001-2011 without exploring the variability within the country. Secondly, we investigate the determinants of persistent and transient inefficiency in the HE literature to provide insights for policymakers (Badunenko and Kumbhakar; 2017). Further, the paper aims to provide empirical evidence about the changes in efficiency in the years following Law 240/2010. As far as we know, the studies in the literature use datasets limited to a few years after the reform.

1.4 Methodology

1.4.1 Efficiency of a Multi-product Organization

Measuring the efficiency of universities requires the definition of their production process. Higher education institutions are regarded as multi-product organizations, with teaching, research, and the third mission as their primary activities (Cohn et al.; 1989).

A convenient way to model such multiple-input and multiple-output technology is to use the notion of distance function (Shepherd; 1970), which consists of a cardinal representation of the production technology that accommodates both multiple-input and multiple-output settings (Chambers and Färe; 2020). Since the inputs of universities are mainly predetermined by government policy (Johnes; 2014), we model the education production technology through an *output-distance function*

$$D_o(\boldsymbol{y}, \boldsymbol{x}) = \min \left\{ \theta \middle| \frac{\boldsymbol{y}}{\theta} \in P(\boldsymbol{x}) \right\}, \tag{1.1}$$

where feasible output set $P(\boldsymbol{x})$ represents the set of all output vectors $\boldsymbol{y}$, which can be produced using the input vectors $\boldsymbol{x}$. Equation (1.1) essentially shows the potential expansion of each output in $\boldsymbol{y}$ when all the inputs are kept at their levels. The distance function is a function of both outputs and inputs, $D_o(\boldsymbol{y}, \boldsymbol{x}) = f(\boldsymbol{y}, \boldsymbol{x}, \boldsymbol{\beta})$, where $\boldsymbol{\beta}$ is the education technology parameter vector to be estimated once $f()$ is specified. The distance function is non-decreasing in output, homogeneous of degree 1 in $\boldsymbol{y}$ and decreasing in $\boldsymbol{x}$ (see Färe and Primont; 1995, for more details). By linear homogeneity restrictions, the outputs can be normalized by an arbitrary output variable, for example, y_1, viz.,

$$y_1^{-1} D_o(\boldsymbol{x}, \boldsymbol{y}) = f(\boldsymbol{x}, \tilde{\boldsymbol{y}}), \tag{1.2}$$

where $\tilde{\boldsymbol{y}} = \left(\frac{y_2}{y_1}, ..., \frac{y_M}{y_1}\right)$. Assuming $e^{-u} = D_o(\boldsymbol{y}, \boldsymbol{x})$, where $u \geq 0$, taking the logs of both sides of (1.2) and rearranging terms, we obtain

$$-\log y_1 = \log f(\boldsymbol{x}, \tilde{\boldsymbol{y}}) + u + \varepsilon, \tag{1.3}$$

where the term u measures the amount of output that can be increased using the same quantity of inputs. Specification (1.3) is made stochastic by adding an error term ε.

1.4.2 Types of inefficiency and their determinants

To distinguish between the structural and institutional inefficiencies and exploit the panel nature of the data, we make use of the four-component SF model recently introduced by Colombi et al. (2014), which accounts for persistent and transient inefficiency while allowing the presence of heterogeneity across institutions

$$-\log y_{1,it} = \log f(\boldsymbol{x}_{it}, \tilde{\boldsymbol{y}}_{it}) + u_{0,i} + u_{it} + v_{0,i} + v_{it} \tag{1.4}$$

where university i is observed in period t and overall inefficiency u in (1.3) is broken down into the time-invariant persistent and the time-varying transient inefficiencies, $u = u_{0,i} + u_{it}$. Note that the overall efficiency is the product of persistent and transient efficiencies, $e^{-u} = e^{-u_{0,i}} \times e^{-u_{it}}$. The transient term (institutional inefficiency) captures changes in inefficiency over the years, providing insights into the managers' abilities in increasing or decreasing efficiency. On the other hand, u_{0i} is the persistent term (structural inefficiency) which represents the component of inefficiency that is constant over time and captures issues that can be attributed to the entire higher education system. The random error term ε, in (1.3) is also split into the time-constant error term v_{0i}, which accounts for unobserved heterogeneity and the usual error term v_{it}.

We study the determinants of inefficiency by specifying heteroskedastic inefficiency terms Badunenko and Kumbhakar (2017). Under the assumption of half-normal distributed inefficiency terms, i.e., $u_{0,i} \sim N^{+}\left(0, \sigma^2_{u_{0,i}}\right)$ and $u_{it} \sim N^{+}\left(0, \sigma^2_{u_{it}}\right)$, we let:

$$\log\left(\sigma^2_{u_{it}}\right) = \alpha_0 + \boldsymbol{\alpha}_1 \ \boldsymbol{z}_{u_{it}} \tag{1.5}$$

and

$$\log\left(\sigma^2_{u_{0,i}}\right) = \rho_0 + \boldsymbol{\rho}_1 \ \boldsymbol{z}_{u_{0i}}, \tag{1.6}$$

where $\boldsymbol{z}_{u_{it}}$ and $\boldsymbol{z}_{u_{0t}}$ are the vector of covariates that determine transient and persistent inefficiency, respectively. Note that the variables in $\boldsymbol{z}_{u_{0t}}$ explain the persistent inefficiency term by varying only among universities as they are time-invariant, while the variables in $\boldsymbol{z}_{u_{0t}}$ change among universities and over time.

1.5 Data and Empirical model

The definition of the empirical model requires specifying a functional form for the distance function. We assume that education production function $f()$ in (1.4) has a translog functional form with two input (x_1, x_2) and two output (y_1, y_2). We include a non-linear time trend to control technological change. Further, we account for regional economic and labor market conditions by adding two external factors represented by z_1 and z_2, viz.,

$$\begin{aligned} -\log y_1 = {} & \beta_0 + \sum_{h=1}^{2} \beta_h \log\left(x_{h,it}\right) + \gamma \ \log\left(\frac{y_{2,it}}{y_{1,it}}\right) \\ & + \frac{1}{2}\left[\sum_{h=1}^{2}\sum_{k=1}^{2} \beta_{hk} \log\left(x_{h,it}\right) \log\left(x_{k,it}\right) + \gamma_2 \ \left[\log\left(\frac{y_{m,it}}{y_{1,it}}\right)\right]^2\right] \\ & + \sum_{h=1}^{2} \delta_{h2} \log\left(x_{h,it}\right) \log\left(\frac{y_{2,it}}{y_{1,it}}\right) + \log z_1 + z_2 + t + t^2 + u_{0,i} + u_{it} + v_{0,i} + v_{it} \end{aligned}$$

Our panel dataset consists of 57 Italian public universities observed over the period 2010-2019. We exclude some institutions from the analysis, resulting in a sample of 570 observations. Specifically, of the 68 public universities, we exclude six Special Schools (e.g. *Scuola Normale di Pisa, Scuola Superiore S. Anna*) due to their highly specialized nature. These institutions involve few students selected through merit-based selective procedures, which may affect the comparison with other public universities due to the difference in the high quality of the students enrolled. We also exclude the two universities for foreign students (*Perugia Stranieri and Siena Stranieri*) and the *Università di Roma il Foro Italico*, as it specializes in sports education. Finally, the *Università di Napoli "L'Orientale"* is not included in the sample due to incomplete bibliometric data. Nevertheless, the sample is highly representative of the Italian HE system, as it contains 84% of Italian public universities in which 86% of all university students are enrolled (data refer to the 2018/2019 academic year). Most institutions are located in the South and Islands (22), while 13 are in central Italy, and 11 are in both the Northeast and Northwest. About 54% of universities have a hospital with no significant regional differences. The universities with multi-site are 45%. Table 1.1 presents descriptive statistics by geographic area for the period of analysis (from 2010 to 2019).

We draw information from three data sources: Statistical Office of the Ministry of Education University and Research (USTAT) provides information on students, graduates, staff, and universities' characteristics (Hospital, Multi-site, and Size). Instead, bibliometric data are extracted from SciVal (by Elsevier Publishing), a tool that uses Scopus data to provide numerous indicators to compare the performance of research institutions. From EUROSTAT, we collected indicators of regional economic and labor market conditions.

In line with the literature, we assume teaching and research as the two main activities of universities (Abbott and Doucouliagos; 2009). Our model comprises two inputs and two outputs reflecting the teaching and research functions. The total number of students enrolled in bachelor's and master's degree programs represents the first input of the university production process (x_1). We count students enrolled on 31 July of the current year. As second input, we decompose the academic staff into professors, associate professors, and researchers, assigning weights to each category based on salary and contribution to teaching and research activities (Madden et al.; 1997; Agasisti; 2016). In addition, we include the number of non-academic staff in the composite indicator by assigning a lower weight. We assign 1 to full professors, 0.75 to associate professors, 0.5 to researchers, and 0.25 to technical staff (x_2). As the output of the process, we first consider the total number of graduates of bachelor's and master's degree courses (y_1). Secondly, we employ a bibliometric measure provided by SciVal that indicates the amount of a university's research products in the top 10% of most cited publications, weighted by field.[1] We consider articles and reviews as publications, excluding conference papers, book chapters, and data papers. Using the entire Scopus database, the index is calculated by sorting publications by citations and year of publication, identifying the highest 10%.

[1] As robustness, we also use 5% and 25% percentiles as thresholds. The results are similar and available on request.

Table 1.1: Descriptive statistics and mean values by geographical areas

		North-east		North-west		Center		South and Islands		Italy	
	Var.	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D	Mean	S.D
N. Students	(x_1)	27107	21008	30779	18778	28486	26555	23699	18321	26815	21180
Weigh. Staff	(x_2)	949	741	957	570	974	894	731	568	873	697
N. Graduates	(y_2)	5493	4471	5862	3625	5008	4633	3793	2922	4798	3901
Research	(y_1)	308	279	337	227	290	291	176	163	259	243
GDP	$(z_{it,1})$	31931	2708	33874	3942	29360	2550	18878	2502	26681	7082
Unemployment	$(z_{it,2})$	6.56	1.01	7.63	1.57	9.51	1.77	17.10	4.09	11.51	5.33
Size	$(z_{it,3})$	2.90	1.17	3.45	1.09	2.53	1.34	2.5	1.60	2.77	1.24
Hospital	$(z_{0,i,1})$	0.73	0.45	0.45	0.50	0.53	0.50	0.50	0.50	0.54	0.50
Multi site	$(z_{0,i,2})$	0.54	0.5	0.81	0.38	0.38	0.49	0.45	0.50	0.52	0.50

Note: Authors calculations on data provided by Italian Ministry of Education, Universities and Research Statistical Office (USTAT-MIUR), Scopus (SciVal), EUROSTAT; (Years 2010-2019).

The threshold is obtained using Field-Weighted Citation Impact (FWCI) to account for fields of research. The choice of output indicator for the university research activity is probably the most critical and debated issue in the literature on university efficiency. Although various proxies are used in the literature, most research opts for indicators based on publications or research grants. The latter proxies are often preferred because it reflects the market value of the research, allowing both the quantity and quality of research to be considered (Johnes; 1997; Worthington; 2001). On the other hand, bibliometric indicators, available in multidisciplinary databases, represent a less ambiguous research output, as research grants are spent on research assistance and other facilities that are input into the production process (Johnes and Johnes; 1993). However, Gralka et al. (2019) comparing efficiency results obtained using research grants and several publication indicators, find a high correlation between the estimated efficiency scores. We use a composite bibliometric indicator that accounts for quantity and quality in the case of Italian universities. Furthermore, by considering the various citation patterns between disciplines, the field-weighted metric enables us to partially account for differences between disciplines. Finally, regional GDP per capita (z_1) and regional unemployment (z_2) operate as indicators of local economic and labor market conditions.

The determinants of persistent and transient inefficiency are analyzed by modeling the variances in (1.5) and (1.6). The content of vectors $\boldsymbol{z}_{it}$ and $\boldsymbol{z}_{0t}$ varies depending on the model specification. Comprehensively, concerning the persistent inefficiency term, we study the effect of having a hospital ($z_{0,i,1}$), being a multi-site university ($z_{0,i,2}$) and the differences between the four geographic areas. For the regional analysis, we follow the ISTAT code which divides Italy into 1) North-West, 2) North-East, 3) Center, 4) South, and Islands. As far as transient inefficiency is concerned, we analyze the effect of regional GDP per capita ($z_{it,1}$), regional unemployment ($z_{it,2}$), and university size ($z_{it,3}$). The university dimension is measured in terms of the number of students. Finally, we examine the variation over time at the national level and in the four geographical areas.

1.6 Empirical results

This section presents the results of the analysis. We first describe the overall efficiency results and examine the persistent and transient components. Next, we analyze regional differences and the catching-up of underperforming universities. A third subsection discusses the effect of local economic conditions on efficiency.

1.6.1 Overall trend, persistent and transient efficiency

Table 1.2 presents four model specifications of the four-component stochastic frontier analysis we applied. The top panel "University production function" displays the estimated coefficients of the university education production frontier. The specifications M1 to M4 differ in the choice of inefficiency determinants analyzed (panel "2. Structural (persistent) inefficiency component:" and "4. Institutional (transient) inefficiency component"), except for M4, where we explore the effect of local economic conditions on the education production frontier. M1 only looks at the dummy variable in the inefficiency specification to see if inefficiency changed after 2015. M2 added area differences to model M1. Model M3 enriches specification by considering the possibility that the change in efficiency occurred gradually rather than abruptly as in M1, which is closer to reality as universities adjusted at various paces. The specification M4 is the richest as it accounts for regional differences in both types of inefficiencies as well as local economic conditions. The coefficients of the education production frontier are significant and fairly stable across specifications.

We discuss the efficiency results because the non-linear nature of the model makes the coefficients not particularly informative. The marginal effects will be discussed below. The four panels, labeled as "1. Random effects component", "2. Structural (persistent) inefficiency component", "3. Random noise component", and "4. Institutional (transient) inefficiency component", demonstrate that all four error components — random effect, persistent inefficiency, random noise, and transient inefficiency, respectively — are significant in all model specifications. This provides compelling evidence in favor of employing the four-component stochastic frontier approach to prevent any potential underestimation or overestimation of efficiency. In order to streamline the selection of models, we will focus on the one that possesses the greatest economic explanatory power by accounting

Table 1.2: University production function.

Parameter	M1		M2		M3		M4	
University production function								
Intercept	3.681	(<1e-9)	3.137	(<1e-9)	5.200	(<1e-9)	4.332	(1e-4)
log(x1)	0.009	(0.910)	0.020	(0.855)	0.154	(0.006)	-0.086	(0.135)
log(x2)	-1.260	(<1e-9)	-1.172	(<1e-9)	-1.642	(<1e-9)	-1.350	(<1e-9)
log(y2/y1)	0.938	(<1e-9)	0.930	(<1e-9)	1.009	(<1e-9)	1.040	(<1e-9)
0.5*log(x1)^2	0.062	(3e-4)	0.022	(0.089)	-0.039	(0.003)	-0.096	(8e-4)
0.5*log(x2)^2	0.168	(<1e-9)	0.134	(<1e-9)	0.159	(<1e-9)	0.082	(<1e-9)
0.5*log(y2/y1)^2	0.096	(<1e-9)	0.098	(<1e-9)	0.092	(<1e-9)	0.092	(<1e-9)
t	-0.065	(<1e-9)	-0.066	(<1e-9)	-0.048	(<1e-9)	-0.048	(<1e-9)
t^2	0.003	(<1e-9)	0.003	(<1e-9)	0.002	(<1e-9)	0.002	(8e-4)
log(x1)∗log(x2)	-0.121	(<1e-9)	-0.088	(<1e-9)	-0.062	(<1e-9)	0.004	(0.563)
log(x1)∗log(y2/y1)	-0.044	(0.146)	-0.028	(0.252)	-0.039	(0.115)	-0.018	(0.575)
log(x2)∗log(y2/y1)	-0.015	(0.456)	-0.023	(0.104)	-0.026	(0.001)	-0.043	(4e-4)
log(GDP)							0.032	(0.742)
Unemployment							-0.003	(0.370)
1. Random effects component: $\log\sigma^2_{v_{0i}}$								
Intercept	-4.110	(<1e-9)	-4.955	(<1e-9)	-4.944	(<1e-9)	-4.983	(<1e-9)
2. Structural (persistent) inefficiency component: $\log\sigma^2_{u_{0i}}$								
Intercept	-5.341	(<1e-9)	-9.693	(0.120)	-9.436	(0.033)	-10.286	(0.157)
Area: 2			-15.777	(0.966)	-3.902	(0.930)	0.825	(0.883)
Area: 3			5.807	(0.345)	5.098	(0.237)	5.934	(0.400)
Area: 4			6.465	(0.297)	5.767	(0.187)	6.799	(0.350)
Hospital university					0.580	(0.188)	0.734	(0.063)
Multi Site					0.510	(0.009)	0.514	(0.099)
3. Random noise component: $\log\sigma^2_{v_{it}}$								
Intercept	-6.287	(<1e-9)	-6.285	(<1e-9)	-6.574	(<1e-9)	-6.630	(<1e-9)
4. Institutional (transient) inefficiency component: $\log\sigma^2_{u_{it}}$								
Intercept	-2.015	(<1e-9)	-2.083	(<1e-9)	-1.230	(7e-4)	-5.285	(0.636)
Size	-1.452	(<1e-9)	-1.430	(<1e-9)	-1.029	(<1e-9)	-0.971	(<1e-9)
Year >= 2015	-0.149	(0.565)	-0.077	(0.764)				
Trend, logged: log(t)					-0.987	(<1e-9)		
Unemployment							0.158	(0.004)
log(GDP)							0.218	(0.842)
log(t) × Area: 1							-0.636	(0.030)
log(t) × Area: 2							-1.976	(0.016)
log(t) × Area: 3							-1.013	(0.004)
log(t) × Area: 4							-1.335	(<1e-9)
Sample Characteristics								
N	57		57		57		57	
$\sum_{i=1}^{N} T_i$	570		570		570		570	
Sim. logL	692.79		704.19		715.09		732.06	

Note: Dependent variable: $-\log(y_1)$. p-values in parentheses.

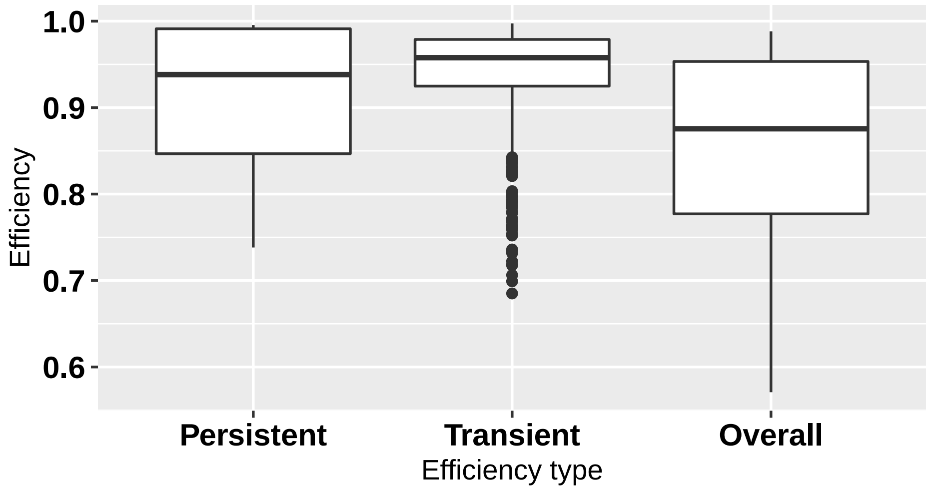

Figure 1.1: Efficiencies

for the most significant variations of inputs, outputs, and control variables. Among the four models considered, M4 is the most comprehensive. Further, M4 also outperforms M3, M2, and M1 from an econometric standpoint. The critical value of the mixed χ^2 distribution with 7 degrees of freedom at the 5% significance level is equal to 15.32, which is smaller than the double difference of the likelihood values of M4 and M3. Therefore, subsequent analysis will rely on the findings obtained from model M4.

Figure 1.1 shows the box plots of the efficiencies for the entire time frame. For ease of comparison, the range on the vertical axis is the same for the three efficiency types. The overall mean efficiency is 86%; meaning that universities could expand their output by 14%. Further, consistent with previous findings very efficient universities coexist with less efficient ones (Agasisti et al.; 2016), as the overall efficiency ranges from about 50% to 99%. Turning attention to inefficiency decomposition, the persistent and the transient component average to 91% and 93%, respectively. These results suggest that disregarding persistent inefficiency could lead to wrong insights as it comprises a large part of overall inefficiencies.

Figure 1.2 presents the time dimension of the university performance. It becomes apparent that if we separate the structural effect (green line) from the overall efficiency (red line), the university production process appears more efficient, as suggested by the institutional component (blue line). This initial result suggests that although university managers can still achieve efficiency gains, several time-invariant factors influence the performance of institutions, requiring improvements in the structure of the whole HE system. Our findings complement those of Agasisti and Gralka (2019), who show that

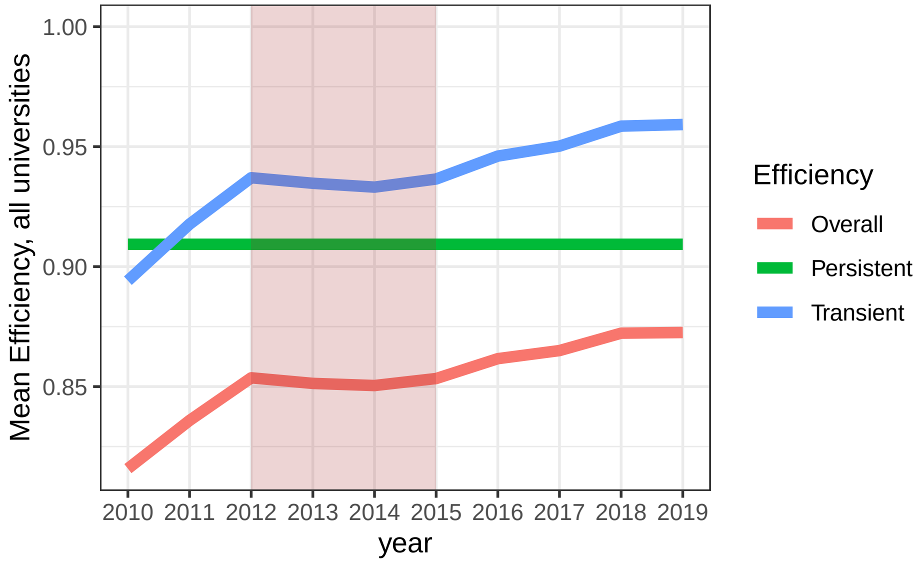

Figure 1.2: Mean Efficiencies

the persistent inefficiency term is much smaller. Our results are not contradictory since the authors analyze the period preceeding the implementation of the Gelmini reform. The changes brought about by legislative interventions have greatly affected universities' activities. In addition, the authors provide efficiency measures in a cross-country comparison, which may influence the university production frontier.

The bottom half of Table 1.2 shows the determinants of structural and institutional inefficiency. The sign of the coefficients indicates the relationships between the variable and the inefficiency term: a parameter with a positive sign in the inefficiency components implies that the inefficiency is larger, thereby reducing university performance

First, considering the determinants of institutional inefficiency, the coefficient $\log(t)$ is negative and statistically significant (specification M3), indicating that efficiency has increased throughout the analyzed period. Figure 1.2 confirms this finding. In particular, it reveals that the overall efficiency increased significantly after the Gelmini reform, slowing down between 2012 and 2015 and then growing more rapidly after 2015. Finally, consistent with previous results (Herberholz and Wigger; 2021), the coefficient of university size (Size) is negative and statistically significant, suggesting that university size is associated with higher efficiency.

Turning to the structural inefficiency component, Table 1.2 shows that the coefficient of the Hospital dummy is positive and significant, meaning that universities with hospitals perform worse. Although never studied in terms of the determinant of structural inefficiency, this result was expected as medical school costs are notoriously higher among all departments (Agasisti and Salerno; 2007). We observe the same effect for universities located in more than one city. The coefficient of the Multisite dummy is positive and statistically significant, suggesting that these universities are less efficient.

1.6.2 Regional differences and Catch-up

As discussed above, the literature so far describes the Italian context as characterized by significant geographical differences in HE efficiency. In the M4 specification, we investigate whether the increasing efficiency trend at the national level is also evident in the four major Italian geographical areas. The $\log(t)$ coefficients in Table 1.2 (specification M4) depict that institutional efficiency is increasing in all regions. Nevertheless, as Figure 1.3 (top panel) shows, the regional gaps are still relevant. However, the disparities are mainly driven by structural efficiency (middle panel), as the differences in institutional inefficiencies (bottom panel) are not as pronounced between regions.

By looking at the figure, we reiterate and strongly advocate considering both types of inefficiency to propose an appropriate policy and promote efficiency improvements: as a result of the performance-based funding system, the new regulatory framework has pushed universities to improve their efficiency to the point of nearly eliminating geographical gaps. The gaps still persist due to structural factors that cannot be changed in the short term and require policy intervention.

Finally, Figure 1.4 displays the average efficiency growth for the four geographical areas between 2010 and 2019. More specifically, the value shown in the year 2011 is the ratio of the efficiency in 2011 to the efficiency in 2010. The value shown in the year 2012 is the ratio of the efficiency in 2012 to the efficiency in 2010. We thus observe the growth rates relative to the beginning of the period. The figure suggests a catch-up process of the poorly performing universities, with institutions in the South and Islands exhibiting the highest growth rate. On the other hand, universities in the Center show the worst response to the changes introduced, particularly during the Gelmini reform's implementation period (between 2012 and 2015). The poorly performing universities have been persistently closing the gap with their better-performing counterparts.

1.6.3 Efficiency and local economic conditions

Specification M4 examines whether GDP per capita and the unemployment rate at the regional level influence the university production frontier. The upper panel of Table 1.2 shows that the coefficients associated with both variables are not statistically significant.

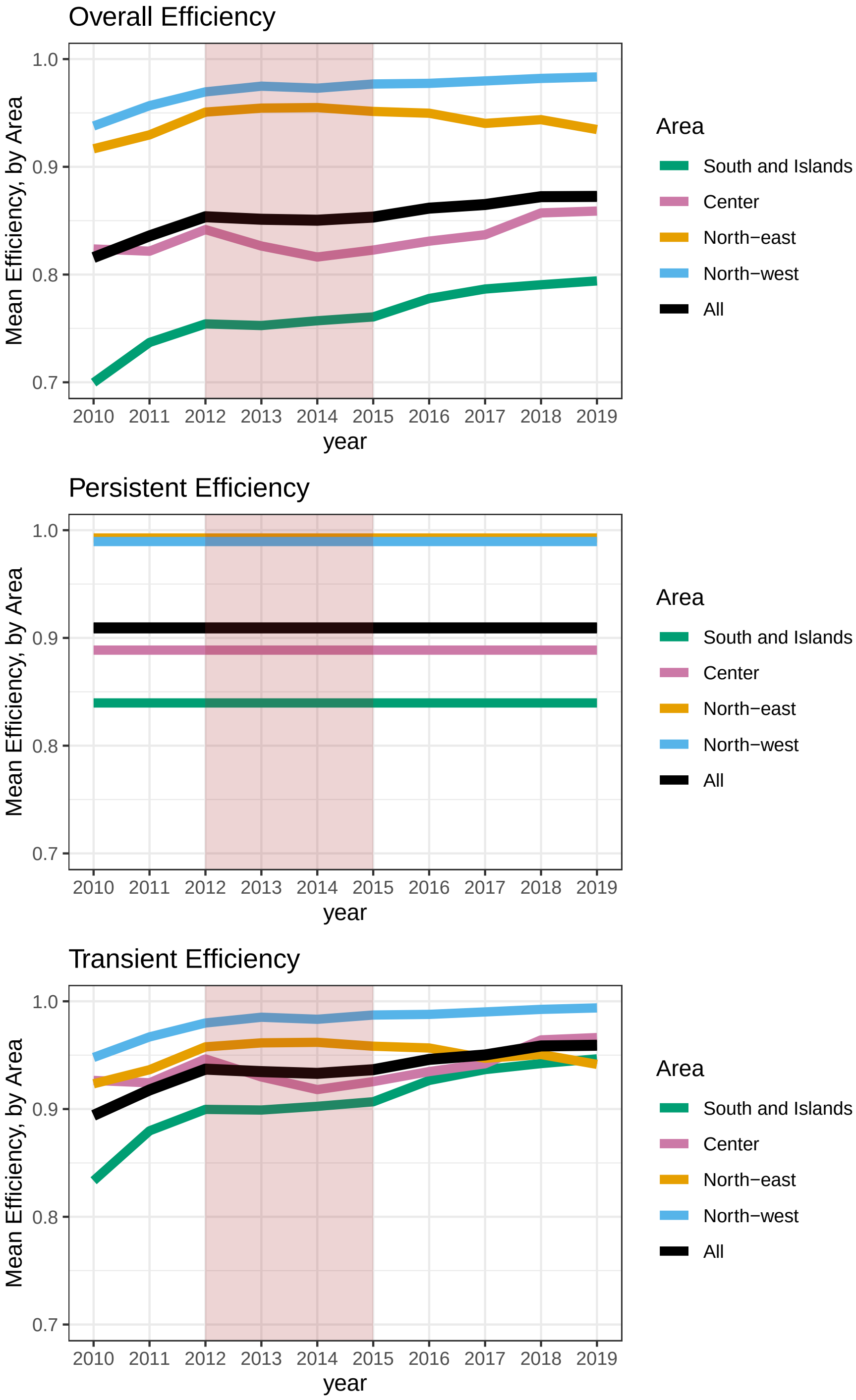

Figure 1.3: Mean Efficiencies by Area

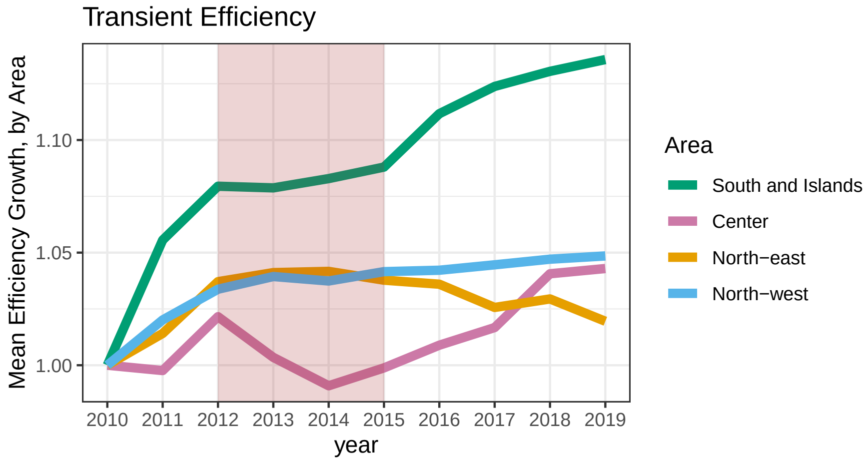

Figure 1.4: Catch-up

It implies that the local economy and labor market conditions do not affect universities' education production technology. However, when considering these indicators as determinants of institutional inefficiency our findings suggest that the unemployment rate plays a crucial role in describing university performance. The bottom half of Table 1.2 displays that while the coefficient of regional GDP is not statistically significant, the unemployment rate increases university inefficiency, as the coefficient is positive and statistically significant. Given that the regional per capita GDP does not affect university efficiency, students appear more interested in finding a job than studying in a wealthy region.

1.7 Discussion and policy implications

Our findings suggest that Italian universities have embarked on a virtuous path concerning the use of public funds. The new regulatory framework appears effective in fostering the efficiency of the Italian HE system, with significant growth in the efficiency of historically underperforming universities. However, we show that the historical north-south regional disparity is still relevant due to structural reasons. This is one of the reasons, we advocate distinguishing between structural (persistent) and institutional (transient) inefficiency components since it is the time-invariant factors and structural conditions that explain regional gaps. More research is desirable both within national HE systems and across countries that share similar characteristics, for example, those that follow the Bologna Declaration (1999). As a minimum, we need to understand the different impacts of regulatory frameworks on universities within the country. Then the attention should be turned to evaluating them in a cross-country context to analyze the regulatory approaches and experiences of various countries.

Back to the Italian case, our results offer significant policy insights. Although the reform appears effective, a further step toward a gain in efficiency requires structural intervention. Multiple structural conditions unrelated to the ability of managers to organize university activities affect, the efficiency of universities. The managers of southern universities are limited in bridging the gap in the *long-run* perspective. The general underfunding of the Italian HE system combined with performance-based funding mechanisms risks leading to and cementing conditions of structural inefficiency. Some universities do not have the financial possibilities to structure their long-term strategic goals being unable to invest in improving their teaching and research.

A further relevant result for policy implementation relates to the effect of local labor market conditions on institutional inefficiency. Universities located in regions with lower unemployment rates perform better. Again, some external conditions impact universities' performance without the responsibility of the institutions themselves. One explanation for this result concerns the student quality and their mobility behavior. The literature shows interregional differences in students' ability scores between Italian regions are also very large (Agasisti and Cordero-Ferrera; 2013). In addition, universities in northern Italy benefit from a high percentage of southern students moving to study in northern regions (ANVUR; 2018). Students willing to migrate are more likely to have higher skills, higher aspirations, and better family backgrounds, an insight from the 'aspiration × attainment × background' model (Marjoribanks; 2003). As a result, some institutions may benefit from having better students, allowing these universities to achieve the same output with less effort. A further explanation comes from evidence that labor market conditions influence the likelihood of timely completion of studies, which tends to increase as unemployment rises due to the lower opportunity costs of education (Contini et al.; 2018). Contextually, labor market conditions can affect structural inefficiency through the funding system. As a result, and counterproductive to narrowing the north-south gap, resource allocation depends in part on factors outside the control of universities, due to enrollment dynamics and the lower ability of students to pay tuition in some regions. Reiterating the usefulness of the performance-based funding mechanism, we endorse a more holistic approach that accounts for structural differences to improve the efficiency of the HE system in all geographical areas.

1.8 Conclusion

This paper studies the efficiency of Italian public universities and the degree of convergence among regions between 2010 and 2019. The Italian case is of particular interest for several reasons. Firstly, in line with the reforms implemented in many European countries, the Italian HE system has undergone a long reform process that introduced performance-based funding mechanisms and changes to the governance system, intending to improve the efficiency of public universities through the introduction of performance-based funding mechanisms and changes to the governance system. Furthermore, Italy is characterized by persistent regional disparities in economic and labor market conditions, which reflect in the education sector.

Methodologically, we address the ignored issue of disentangling structural (persistent) and institutional (transient) efficiency while accounting for unobserved heterogeneity. Our findings provide valuable insights. First, we demonstrate that the efficiency of Italian universities increased over the entire period under analysis, indicating that the new regulatory framework is providing the appropriate incentives for universities to use public funds effectively. Second, the significant efficiency growth rate observed in institutions in the South and Islands implies that traditional underperforming universities are making progress in catching up. However, there are still significant regional differences in overall efficiency. Our methodology allows us to identify that a considerable proportion of inefficiencies can be attributed to structural factors that remain constant over time. Lastly, we find that higher regional unemployment rates are associated with lower efficiency in universities. For these reasons, we recommend using our methodology to account for persistent inefficiencies to avoid erroneous policy implications and evaluations.

Further research opportunities could be explored concerning the limitations of our study. The absence of reliable quality measures is well-know a shortcoming of the literature on HE efficiency. In this paper, we partially contribute to the issues by exploiting a mixed qualitative and quantitative indicator of research output. Due to the lack of data, we do not account for the quality of teaching in efficiency estimation. This limitation opens up further research possibilities, such as investigating the relationship between unemployment and inefficiency by studying the connection between student quality, mobility choice, and university efficiency.

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Chapter 2

Policy responses to COVID-19 and the efficiency of Italian universities*

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Abstract

In response to the COVID-19 pandemic, the Italian government has increased public support for universities. While this influx of financial resources could partially mitigate some negative impacts of the pandemic on outputs, it also significantly increases inputs and costs for universities, potentially leading to a temporary loss of efficiency. This paper examines the policy effect of increased funding on universities' efficiency in Italy. By focusing on both production and cost efficiency, we utilize a panel dataset spanning five years (2017–2021) and employ the recently developed Generalized True Random Effect stochastic frontier model. This model enables us to decompose overall inefficiency into persistent and transient components while accounting for heterogeneity across institutions. Our findings reveal that while production efficiency has remained relatively stable over the years, post-COVID-19 is characterized by a statistically significant decrease in cost efficiency. This result indicates a reversal of the positive efficiency trend observed in Italian universities in recent years. Moreover, we identify a homogeneous reduction in cost efficiency across geographic regions, suggesting that the negative effect is unrelated to specific initial conditions or management decisions in the short run.

2.1 Introduction

The COVID pandemic posed numerous challenges to higher education institutions, especially from the perspective of guaranteeing the continuity of teaching and research services (Marinoni et al.; 2020). Universities reacted through an intensive use of technology for digital learning, as well as with extraordinary efforts to maintain the research activities with a lot of dedication by its researchers, staff, and professors (Agasisti and Soncin; 2021). Given the high level of human capital involved in their processes (educated

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students, well trained professionals, and academics) the universities were well positioned to maintain their levels of operations without suffering an excessive level of disruption, as instead happened for K12 schools. As a matter of fact, there is little evidence of those learning losses that have been documented in the primary, middle and high schools (Donnelly and Patrinos; 2021).

Some governments decided to sustain and accompany the universities' efforts to contrast COVID threats by means of specific policies. In this paper, we focus on the case of Italy, which is very interesting because the country was one of those most affected (and earliest) by the pandemic. Indeed, the Italian government decided for one of the longest lockdown periods in the whole Europe, forcing university classes to be held online for many months, and academics not to attend their offices and laboratories for a long period. At the same time, the government invested a huge amount of money in the university sector. Approximately, the overall amount of new public resources devoted to the HE sector has been €367 million in 2020 and €958 million in 2021[1]. This represents an increase of 2.8% and 7.3% over the pre-existing budget in their respective years. Such extraordinary injection of financial resources happened both in the immediate weeks during the pandemic and in the subsequent months, also leveraging upon the resourced made available through the EU's Recovery and Resilience Plan (RPP). The most part of the new resources have been used for (i) increasing the number of researchers and professors, (ii) renewing the facilities with technology for favouring hybrid and online learning, (iii) funding big research projects, and (iv) increasing the number of residential places for students. The intention of the policy makers was clear: the financial resources should be used to avoid a decrease in the quality and quantity of universities' activities, which would irremediably harm the economic and social development of the country in the medium-long run. This fear is well understandable, especially given the well-known crucial role of HE for the country's development (Lucas Jr; 1988; Valero and Van Reenen; 2019; Agasisti and Bertoletti; 2022) – although it has been noted how expanding HE, per se, is not going to contribute to economic growth without increasing the cognitive skills (Hanushek; 2016). Considering the significant financial investment and the gravity of COVID-19's impact on Italy and its education systems, the Italian case is particularly noteworthy. Specifically, the findings outlined in our study shed light on a mechanism that may operate in other European countries, albeit it is likely to be less pronounced or mitigated by different contextual factors.

The potential overall effects of this policy – namely, investing more resources in the field – on universities' performance, therefore, are not clear a priori. This is a particularly

[1]See the Section 2.3 for additional details on the specific policy actions

relevant topic if we consider the definition of efficiency as a measure of performance. Efficiency might be initially defined here as the ratio between outputs (for example, number of graduates and academic publications) and inputs (human, financial and structural resources) – see Agasisti (2023). From a theoretical perspective, there are three possible outcomes of the policy on universities' efficiency. First, resources can help universities to maintain their pre-COVID level of operations. In other words, the additional financial investments are strictly necessary to avoid that universities systematically reduce their teaching and research outputs (for instance, the number of graduates and publications). According to this view, the net effect of the policy would be a decrease in the efficiency: universities produce the same level of output than pre-COVID (year $t^* - 1$, with t^* being the COVID year) and the amount of resources absorbed for this purpose is higher. A second option is that the universities could have used the resources for generating an increase of output production, that is proportional to the additional money received. If this is the case, universities can produce more graduates and more research, using the additional money for this purpose. In this case, the level of efficiency should remain stable at the pre-COVID (year $t^* - 1$) level. A third option, however, is that universities can combine the use of new resources in a productive – efficient – way, producing proportionally more graduates and research than the increase of the new available public money. There can be several mechanisms explaining such dynamic, for example because the universities do invest the new money in technology and other innovations that can make the research activities more productive and the teaching experience more effective. If this is the realized scenario, then the efficiency level of universities after COVID might be higher than that of pre-COVID (year $t^* - 1$). A graphical illustration of the potential different effect of the sudden increase of resources for the government policy is reported in the Figure 2.1. Two notes are needed here. In the figure, a constant efficiency level is assumed in the period of years before COVID, but this is not a necessary condition for the theoretical reasoning to hold. Moreover, in this paper we use data for three years before COVID, so the COVID year (t^*) here is reported as $t + 3$ – with t being the first year of data used in the empirical analysis.

Most probably, the various Italian universities have followed patterns of using COVID resources that are quite heterogenous, and different each other. In the paper, we provide estimations of efficiency differentials pre- and post-COVID for each Italian university. Nevertheless, we are interested in estimating a system-level change in efficiency after COVID, so we also provide results about the general modification of performance, costs and efficiency in the entire Italian HE sector. In other words, we pay attention to the "average" and "cumulated" effects of the increase in resources more than to single-institution effect, although estimated separately. In the light of these considerations, this paper aims at answering the following research question: what was the policy effect of increasing financial funds HE after COVID on universities' efficiency, in Italy?

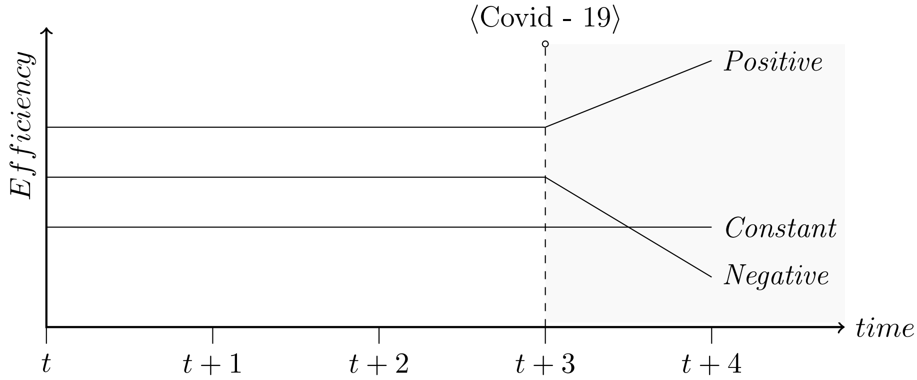


Figure 2.1: University efficiency

Given official data availability, the estimation is limited to short-run effects (specifically, in the year just immediate after COVID, 2021/22). While this could be considered a limitation of the paper, it is worth highlighting that this study represents the first research investigating the effect of COVID-19 disruption on the efficiency of universities. The topic is particularly important since, compared to previous reforms aimed at increasing efficiency or reducing costs of higher education institutions, the intent in this case was considerably different. Given the emergency situation, the priority was indeed to maintain a similar level of outputs, even if this meant increasing the expenditure of higher education institutions.

The research question is investigated by using a Stochastic Frontier (SF) analysis, with both production and cost efficiency models. The SF approach has been preferred over the non-parametric alternative, such as Data Envelopment Analysis, primarily due to its compatibility with the recently developed Generalized True Random Effect (GTRE) SF model (Colombi et al.; 2014). This technique, unavailable for non-parametric approaches, is particularly suited to the context of the study as it can decompose overall inefficiency into persistent (long-term structural inefficiency not affected by COVID-19) and transient (short-term inefficiency capturing the effect of COVID-19 on university performance) components.

The remainder of the paper is structured as follows. Section 2.2 reviews the main literature which is relevant for this research. Section 2.3 provides a context and institutional background about the COVID policies for Higher Education in Italy. Section 2.4 outlines the empirical strategy adopted, while section 2.5 illustrates the available and used data. Section 2.6 reports the results. Section 2.7 concludes, along with deriving policy implications.

2.2 Literature

2.2.1 The effect of policy reforms and economics shocks on efficiency of university

The topic of university efficiency has received considerable attention in recent decades. Within this literature, several papers have looked at the effects of external shocks on the efficiency of higher education institutions. Notably, various studies have evaluated the effects of policy reforms or interventions on efficiency of public services, as outlined in the systematic literature review of Mergoni and De Witte (2022). In the specific field of education, these works have mainly investigated the consequences of funding policies (Chang et al.; 2009; Tochkov et al.; 2012; Schubert and Yang; 2016; Carrington et al.; 2018; Berbegal-Mirabent; 2018), initiatives aimed at enhancing teaching or research quality (Chang et al.; 2009; Zhang et al.; 2011; Montoneri et al.; 2012; De Witte et al.; 2013a,b; Yang et al.; 2018), and university mergers Glass et al. (2006); Papadimitriou and Johnes (2019).

Efficiency research has also focused on assessing the impact of economic shocks on university efficiency. For example, Martínez-Campillo and Fernández-Santos (2020) examine the effects of the economic crisis on public universities in Spain. Using a two-stage Data Envelopment Analysis (DEA), the authors demonstrate that higher education institutions became more efficient during the crisis, albeit with significant heterogeneity across regional locations. Similarly, Lehmann et al. (2018) investigate the effects of the economic crisis on German and Italian public universities. The results indicate that Italian universities performed better during the crisis compared to their German counterparts, although the crisis itself did not show a significant average impact on efficiency.

When analysing the effects of these phenomena, it is crucial to understand their nature and objectives. Agasisti and Haelermans (2016) show how the efficiency of universities can be strongly driven by the specific policy perspective implemented. In particular, the set of funding rules utilised to finance public universities in a country significantly influences the desired performance outcomes (Agasisti and Haelermans; 2016). Similarly, university mergers may be precisely motivated by the objective of enhancing the efficiency of higher education institutions (Bösecke; 2009; Aarrevaara et al.; 2009).

During the economic crisis, budget constraints and austerity measures may have directly or indirectly compelled universities to become more efficient and productive in their use of public resources, as well as to be accountable to society for their actions (Martínez-Campillo and Fernández-Santos; 2020). In such cases, the desired outcome is exactly to improve university efficiency. On the other hand, in emergency situations, the policy objectives can be entirely different. As we will discuss in more detail later, in the case of COVID-19, most European governments have increased public support to universities to ensure equal and adequate education for every student, and the potential effects on efficiency were considered a second-order problem.

2.2.2 COVID-19 effects on efficiency of universities

Previous studies on the impact of emergencies on efficiency, particularly in the field of education, are relatively scarce. However, it is noteworthy to mention the study conducted by Olanubi and Olanubi (2022), which examined the efficiency of government spending on health in 19 EU countries during the global pandemic. Evan if the context of their exploration is different from our studies the theoretical approach and the conceptual problem as several similarity. Their findings revealed that approximately 5% of the allocated funds for health were inefficient. This highlights the potential risk of inefficiency in public funding during the emergency caused by the COVID-19 pandemic.

Conversely, there is an extensive body of literature on COVID-19 and its effects on different dimensions of higher education. This literature provides valuable insights into the mechanisms driven by the pandemic that could potentially impact the efficiency of universities. In this section, we propose an ample review of this literature. We refer to existing studies with a global perspective, not limiting the analysis to the Italian case.

Teaching outputs

The available evidence regarding the impact of the COVID-19 pandemic on the number of graduates or graduation rates (i.e., key indicators when measuring university efficiency) is still inconclusive. Several studies have pointed out the adverse effects of the pandemic on students' well-being and motivation (Copeland et al.; 2021). The lack of social interaction, which has affected especially older students, along with the emergency situation, appears to have increased stress and anxiety levels of the young adults (Dodd et al.; 2021; Machado et al.; 2023). The negative effects on well-being may result in low motivation and engagement, consequently increasing the risk of dropout, particularly for those already at a higher risk of educational disengagement (Fan and Wolters; 2014). Additionally, the pandemic has caused economic instability and uncertainty, creating

barriers for planning and investing in education, especially for low-income households, as reported by Luppi et al. (2021). Finally, the limited access to technology and support from educators also posed significant barriers to the effectiveness of remote learning (Di Pietro et al.; 2020; De Witte and François; 2023).
On the other hand, remote learning has introduced flexibility that can be advantageous for higher education participation (see Gonzalez et al.; 2022). It has the potential to make education more accessible to students who previously faced barriers to attending traditional schools or universities. For instance, students living in remote or rural areas may find it challenging to attend physical institutions due to distance and travel time. In such cases, online education provides an effective alternative, allowing students to access education from their homes (Sadeghi; 2019; Cheng et al.; 2007). Remote learning also allows students to stay in their family houses, potentially reducing household costs associated with renting accommodation for attending universities outside their city. Similarly, it saves time for students who would otherwise commute to their universities (Cheng et al.; 2007). Working students can also find new ways to combine their work schedules with university obligations, such as accessing recorded lessons online at their convenience (Murphy et al.; 2013).

The extent to which the COVID-19 pandemic directly impacts graduation outcomes remains relatively unexplored. Although limited in number, existing studies tend to suggest a negative association, even though a definitive answer cannot be provided. A study conducted by Aucejo et al. (2020) finds that 13% of students delayed graduation due to COVID-19, and lower-income students were 55% more likely to have delayed graduation than higher-income peers. Moreover, a survey at the University of La Laguna (Spain) by López-Aguilar et al. (2022) reveals a significant proportion of students contemplating abandoning their university education, especially in social science courses, where the intention to leave was nearly 40%. This negative effect is also confirmed by Jacobo-Galicia et al. (2021), who have found a link between the fear of COVID-19 and university dropout rates in Mexico, while Moscoviz et al. (2022) provide evidence of increased student dropouts among adolescents in low-income countries after the pandemic. In contrast, A survey by Farcnik et al. (2022) among Slovenian university students reveals that less than 7% considered dropping out for the labor market, with the majority preferring to continue their studies.

It is important to acknowledge that the impact of COVID-19 may have varied across different fields of study. For example, certain disciplines like medicine and nursing may have witnessed an increase in the number of graduates due to the urgent need for healthcare professionals in the face of the pandemic and the strain it placed on hospitals. In countries such as Italy, where there was a shortage of medical personnel, measures were implemented to expedite the training of doctors, including streamlining the procedures for medical schools to produce more physicians (Ferrario et al.; 2020)[2].

Research outputs

The existing literature tends to underscore various factors that can contribute in negatively affect the research productivity during the COVID-19 pandemic. One significant barrier has been the disruption of research infrastructure, with laboratory closures and the suspension of research studies becoming necessary due to the pandemic (Myers et al.; 2020). Furthermore, the adaptation to remote team dynamics, sub-optimal home working environments, balancing work and home obligations, the direct impact of psychological stress on work performance, the lack of regular meetings, and the inability to conduct field visits for primary data collection have all been identified as additional deterrent (Carr et al.; 2021; Shoukat et al.; 2021).These disruptive changes, coupled with the widespread cancellation of academic conferences and delays in institutional review board approvals and peer review processes by academic journals, have posed further challenges for researchers in initiating, completing, and disseminating their research findings (Carr et al.; 2021). Ojo et al. (2023) conducted interviews with 248 academics in South Africa, and their findings showed that two-thirds of the participants either experienced a reduction in productivity or reported no research productivity at all. Similarly, a study by Myers et al. (2020) reveal that faculty members have, on average, faced a 24% decrease in research productivity since the beginning of the COVID-19 pandemic and the subsequent shutdown of research operations. Among laboratory-based scientists, the impact has been even more pronounced, with a decline in productivity ranging from 30% to 40%.
On the other hand, it appears that certain fields of research have benefited from the pandemic. Kruger et al. (2020) highlight that research productivity in economics and finance increased by 35% after the onset of COVID-19, even excluding COVID-related research. This increase has been particularly pronounced in top research departments and among younger researchers (below 35 years old). These productivity gains can be attributed to various factors. Firstly, the pandemic itself has presented a highly captivating phenomenon to explore across diverse research areas, serving as a strong motivation for the advancement of new studies. Researchers have been driven to investigate the economic and financial implications of the pandemic, leading to increased productivity

[2] As an example, the Italian Government grants automatic approval of medical licenses to medical graduates awaiting their license examination. This enables them to be employed in hospital wards (Ferrario et al.; 2020).

in these fields. Secondly, the widespread adoption of digital communication tools in universities has facilitated enhanced communication and collaboration among academics. The use of virtual platforms and online resources has streamlined the research process, enabling researchers to connect and work together more effectively. This improved collaboration has ultimately strengthened scientific outputs and contributed to the overall increase in research productivity (Kruger et al.; 2020). However, it is important to note that the effects of the pandemic have demonstrated heterogeneity across gender and age groups. In the study of Kruger et al. (2020), no productivity gain has been observed for middle-aged women, possibly due to increased burdens of family duties. This finding is also supported by the study conducted by Amano-Patiño et al. (2020), which revealed that women, especially mid-career female economists, were underrepresented in COVID-related research.

Universities' inputs In terms of inputs, the COVID-19 pandemic has had a significant impact on public funding for higher education institutions. In response, several European countries have taken measures to mitigate the potential negative effects by providing additional financial support or establishing emergency funds. These initiatives have primarily focused on supporting students, particularly those from disadvantaged backgrounds. In most cases, funds were directly allocated to students through grants and financial compensation[3]. However, these initiatives indirectly helped universities mitigate the potential adverse effects of the pandemic on university revenues derived from student fees. Additionally, governments have implemented direct subsidies to universities aimed at supporting research activities. For example, the Portuguese government dedicated around 7 million euros in 2020 to foster research in the field of COVID-19[4]. Also, in 2021, the Netherlands allocated 76 million euros for a new program to enable temporary researchers to complete their research and make up for delays caused by the COVID-19 crisis[5].

Another crucial aspect of direct financial support to universities has been the upgrading of digital technologies to facilitate remote and blended learning necessitated by the pandemic. For instance, in 2020, Greece introduced a new fund of 250,000 euros to enhance the electronic infrastructure of universities [6].

In the subsequent section, we will describe the specific circumstances of Italy and

[3]See, for instance, *law Kamerstukken II 2019/20, 35300 VIII, nr. 184 and Kamerstukken II 2019/20, 35464, nr. 1* in Netherlands; and *law CLASS 602-01 / 19-03 / 00087* in Croatia.

[4]See *Diário da República, 2.ª série — N.º 110.*

[5]See *Spoedwet OCW COVID-19 2021 Kamerstuk 35 836 Nr.7 en Bestuursakkoord Nationaal Programma Onderwijs.*

[6]See Greek normative 2020SE34510411

examine the government's policies and funding interventions undertaken to tackle the challenges posed by the COVID-19 pandemic.

2.3 Italian policy context in the context of COVID-19 and higher education

Italy, like many other European countries, has witnessed a substantial implementation of funds in response to the crisis. Notably, probably due to the severity of the pandemic compared to its European counterparts, Italy has devoted a particularly high level of public financial support. Indeed, Italy was the first European country to deal with the COVID-19 pandemic and it was affected by one of the longest school closure in the world (UNESCO; 2020).

From March 2020 until the commencement of the autumn semester, universities adapted by delivering all teaching activities in a fully online format. As the academic year 2020/2021 progressed, universities began implementing blended teaching systems, allowing students to attend classes either remotely or in person. While the specific approaches varied among universities, the overall trend was towards a combination of online and in-person instruction (a tendency that survived after COVID-19).

In response to the significant disruptions caused by the COVID-19 pandemic, the Italian government has implemented various interventions aimed at supporting universities through the provision of public funding. One main area of intervention is the Fund for the regular financing of universities (FFO). Between 2020 to 2022, Italian government increased by almost €700 million the Fund for FFO of universities to help the institutions in coping with the pandemic[7]. The purpose of this increased funding was explicitly focused on supporting two main areas: students and research. Student support was implemented, for example, by increase the number of scholarship of university tax exemptions or by extending the length of PhD scholarships. Also, Italian government established in 2020 an emergency fund for higher education system that was increased during the years, until covering €190 million in March 2021[8]. This fund had the main idea to allow universities to support students who need services or resources to access distance education and research. Instead, public funding to research activities was general intent of supporting the research activity of the departments. For instance, an increase

[7] See *D.L. 34/2020 (L. 77/2020: art. 236, co. 3), D.L. 34/2020 (L. 77/2020: art. 236, co. 5), D.L. 34/2020 (L. 77/2020) (art. 238, co. 5), D.L. 137/2020 (L. 176/2020: art. 21-bis), D.L 2021 (L. 178/2020: art. 1, co. 518), D.L. 34/2020 (L. 77/2020) (art. 238, co. 5).*

[8] See *D.L. 18/2020 (L. 27/2020: art. 100, co. 1), D.L. 34/2020 (L. 77/2020: art. 236, co. 1), D.L. 41/2021 (art. 33).*

of €250 million has been allocated to the Investment Fund in Scientific and Technological Research (FIRST) for 2021 to fund projects of significant national interest (PRIN projects)[9].

Funding for Italian universities has extended beyond strict financial support. For instance, €250 million has been allocated to recruit new university researchers, starting from 2021[10]. The Italian Government has also taken action to address the infrastructure needs of universities. One notable intervention involves an increase in funding for sports activities and facilities in higher education institutions (with a maximum of 10 million euros)[11]. This initiative aims to address the damages incurred during the COVID-19 emergency, which were exacerbated by the lack of maintenance and limited use of these facilities.

This influx of financial resources, coupled with investments in infrastructure and personnel, presents a dual effect. While it could partially mitigate some negative impacts on outputs, it also results in a significant rise in inputs and costs for universities, potentially leading to a temporary increase in inefficiency, if outputs do not increase at the same pace.

2.4 Empirical strategy

Production and cost models are frequently employed in economic literature to assess the efficiency of HEIs. The production approach (equivalently through the production, transformation, or distance function) focuses on the technical relationship between inputs and outputs. In contrast, the cost function describes the minimum cost of producing goods or services with given input prices and technology. Although, under certain regulatory conditions, for example homogeneous pricing of production factors, the cost and production functions provide an equivalent description of the technology, the two approaches convey different paces of information. Policymakers can benefit from both models to address relevant economic issues. Production models, focusing on the technical relationships between inputs and outputs, offer a deeper understanding of the university process and provide insights into possibility of inputs substitution or university merger policies (Papadimitriou and Johnes; 2019). On the other hand, cost functions allow us to assess whether universities can reduce costs while maintaining the same outputs. This last aspect is particularly relevant in the context described above, where public funding has increased substantially in response to the pandemic crisis.

[9]See *D.L. 34/2020 (D.L. 34/2020 (L. 77/2020) (art. 238, co. 4)).*
[10]See *D.L. 34/2020 (D.L. 77/2020) (art. 238, co. 1-3).*
[11]See *D.L. 34/2020 (L. 77/2020: art. 182, co. 1-bis e 1-ter).*

To examine the possible short-term effects of the COVID-19 pandemic on university efficiency, we measure both production and cost efficiency using Stochastic Frontier (SF) analysis. We make use of the recently developed Generalized True Random Effect (GTRE) SF model (Colombi et al.; 2014), which allows us to decompose the overall inefficiency into a persistent (long-term) and a transient (short-term) component while accounting for heterogeneity across different institutions. Distinguishing between these two components is particularly pertinent within the specific context of our paper. Persistent inefficiency refers to long-term operational problems that, in the context of higher education, can be traced to the regulatory system and long-term goals. Conversely, transient inefficiency refers to operational decisions that affect operations each year and are entirely attributable to the management of the specific university (Agasisti and Gralka; 2019). In the context of our analysis, differentiating between the components of inefficiency allows us to understand how the COVID-19 pandemic may affect the efficiency of universities, accounting for both short- and long-term effects. With only one year of observation after the pandemic, all of the variability in inefficiency is captured by the transient inefficiency term, leaving the persistent term to account for structural inefficiencies that existed prior to the pandemic.

A general formulation of the GTRE model can be written as

$$y_{it} = x_{j,it}\beta + v_{0i} - \rho\ u_{0t} + v_{it} - \rho\ u_{it}, \tag{2.1}$$

where $i = 1, ..., n$ denotes the university and $t = 1, ..., T$ indicates the time period. According to model specification (cost or production model), the outcome variable y_{it} is the logarithm of output (or cost); $x_{j,it}$ is a row vector of j inputs (or outputs) and β is the associated vector of parameters to be estimated. In addition to the classical random noise v_{it}, a heterogeneity term v_{0i} capturing institutional differences at the individual level is added to the model. These factors should capture institution-specific differences that are not directly related to efficiency. Furthermore, the overall inefficiency is broken down into the persistent u_{0i} and transient u_{it} inefficiency. Finally, ρ is a known parameter equal to -1 for the production model and 1 for the cost model.

To investigate whether the variation in the inefficiency over the years is statistically significant, we follow the Badunenko and Kumbhakar (2017) approach, introducing the determinants of inefficiency via variance term. Under the assumption of half-normal distributed inefficiency terms, i.e., $u_{0,i} \sim N^+\left(0, \sigma^2_{u_{0,i}}\right)$ and $u_{it} \sim N^+\left(0, \sigma^2_{u_{it}}\right)$, it is possible to specify the transient inefficiency term as heteroskedastic and model the variance $\sigma_{u_{it}}$

as:

$$\log\left(\sigma^2_{u_{it}}\right) = \alpha_0 + \alpha_1\, z_{u_{it}}, \tag{2.2}$$

where $z_{k,u_{it}}$ is the vector of k covariates determining transient inefficiency. This formulation enables the inclusion of time dummy variables in the model specification, allowing us to assess the statistical significance of changes in transient inefficiency. We obtain parameter estimates using a simulated maximum likelihood estimator after specifying the empirical model and assuming a functional form.

2.4.1 Output distance function model

Measuring production efficiency requires the definition of the university production process. Higher education institutions are commonly recognized as multi-output, multi-input organizations (Cohn et al.; 1989). To characterize such a process, we employ the notion of a distance function, which serves as a cardinal representation of the production technology, illustrating the potential expansion of each output while keeping all inputs at fixed levels (Chambers and Färe; 2020). Therefore, we model the university production technology through an *output-distance function*,

$$D_o(y, x) = \min\left\{\theta \middle| \frac{y}{\theta} \in P(x)\right\}, \tag{2.3}$$

where feasible output set $P(x)$ represents the set of all output vectors y, which can be produced using the input vectors x. Equation (2.3) essentially shows the potential expansion of each output in y when all the inputs are kept at their levels. The distance function is a function of both outputs and inputs, $D_o(\ y, x) = f(y, x, \beta)$, where β is the education technology parameter vector to be estimated once $f()$ is specified. By linear homogeneity restrictions, the outputs can be normalized by an arbitrary output variable, for example, y_1, viz.,

$$y_1^{-1} D_o(x, y) = f(x, \tilde{y}), \tag{2.4}$$

where $\tilde{y} = \left(\frac{y_2}{y_1}, ..., \frac{y_M}{y_1}\right)$. Assuming $e^{-u} = D_o(y, x)$, where $u \geq 0$, taking the logs of both sides of (3.3) and rearranging terms, we obtain

$$-\log y_1 = \log f(x, \tilde{y}) + u + \varepsilon, \tag{2.5}$$

where the term u measures the amount of output that can be increased using the same quantity of inputs.

Defining the empirical model requires the specification of a functional for the distance function as well as identifying output and input proxies for the production process.

Following previous studies, we consider teaching and research as the primary functions of universities. Consequently, our production frontier model includes two inputs and two outputs, each corresponding to these activities. The first input (x_1) is represented by the total number of students enrolled in bachelor's and master's degree courses. As the second input (x_2), we use the total academic staff (professors, associate professors, and researchers). The teaching output is represented by the total number of graduates from bachelor's and master's courses (y_1), while the research output ($y_{2_{t+1}}$) is measured in terms of number of publications. The choice of an appropriate research output proxy remains controversial in the literature. Some studies rely on competitive research grants as a quality-adjusted measure of research activities (Johnes; 1997; Worthington; 2001). However, in our setting, given the substantial increase in university financial resources during the pandemic years, including research funding, we argue that it is more appropriate to use a bibliometric measure. This measure is less ambiguous and less affected by the shock of resources entering the system. When dealing with bibliometric measures, it is also crucial to consider that there is a certain time lag between the research activity and the publications. One year's publications are likely related to the productive processes of the previous year. To account for this delay, we use the number of publications at year $t + 1$[12]. For example, publications in 2021 are attributed to the 2020 production process.

Finally, to obtain the empirical specification we assume a translog functional form for the distance function, consistent with recent literature on university efficiency. The output distance function takes the following form,

$$\begin{aligned} -\log y_1 = {} & \beta_0 + \sum_{h=1}^{2} \beta_h \log(x_{h,it}) + \gamma \ \log\left(\frac{y_{2,it}}{y_{1,it}}\right) \\ & + \frac{1}{2}\left[\sum_{h=1}^{2}\sum_{k=1}^{2} \beta_{hk} \log(x_{h,it}) \log(x_{k,it}) + \gamma_2 \ \left[\log\left(\frac{y_{m,it}}{y_{1,it}}\right)\right]^2\right] \\ & + \sum_{h=1}^{2} \delta_{h2} \log(x_{h,it}) \log\left(\frac{y_{2,it}}{y_{1,it}}\right) + \alpha \ t + u_{0,i} + u_{it} + v_{0,i} + v_{it} \end{aligned} \tag{2.6}$$

where university i is observed in period t, and overall inefficiency u in (2.5) is broken down into the time-invariant persistent and the time-varying transient inefficiencies, $u = u_{0,i} + u_{it}$. Note that the overall efficiency is the product of persistent and transient efficiencies, $e^{-u} = e^{-u_{0,i}} \times e^{-u_{it}}$. The dependent variable $\log(y_1)$ is negative as we impose

[12] The analyses are also performed using the number of publications at year t. The results are robust and shown in Section 2.6.

homogeneity restriction by normalising the outputs by an arbitrary output variable. The negative sign for the dependent variable $-\log(y_1)$ implies that ρ in equation (2.1) is positive, as for the cost model. This is only a notational choice with no difference in efficiency estimation. Finally, we include a linear time trend to control for technological change t, and α, β, and γ represent unknown parameter vectors to be estimated.

2.4.2 Cost frontier model

The cost function describes the relationship between the cost of producing outputs given a set of inputs. The overall cost of universities C_{it} can be modeled as,

$$C_{it} = f(y_{j,i}), \tag{2.7}$$

where $y_{j,it}$ is the vector of j outputs produced by the ith university i. As for the production model, we consider teaching and research as the two main activities of universities. Teaching output is represented by the total number of graduates from bachelor's and master's courses. In order to adequately deal with the differences that subjects have on university costs (Agasisti and Salerno; 2007), we differentiate the teaching output according to three subject groups: humanities and social sciences (y_{1h}), natural sciences (y_{1s}), and medicine (y_{1s}).[13] Research output $y_{2_{t+1}}$ is measured by the total number of publications. While various academic disciplines may also influence university costs for research activities, we opt to use the total number of publications as an output measure without distinguishing between specific disciplines. This choice is motivated by the need to constrain the number of parameters to be estimated. Nevertheless, we conduct a robustness analysis by differentiating publications within the same subject mix employed for teaching activities. The results are robust and are presented in Section 2.6. Assuming a translog functional form with four outputs (y_{1h}, y_{1s}, y_{1m}, y_2) we obtain,

$$\begin{aligned}\log C_{it} = \alpha_0 &+ \sum_{j=1}^{4} \beta_j \log(y_{j,it}) + \frac{1}{2}\sum_{j=1}^{4} \beta_j \log(y_{j,it})^2 \\ &+ \sum_{k=1}^{4}\sum_{j=1}^{4} \gamma_{kw} \log(y_k, it) \log(y_j, it) \\ &+ \delta\ z_{1,i} + u_{0,i} + u_{it} + v_{0,i} + v_{it}.\end{aligned} \tag{2.8}$$

[13] *Humanities and social sciences* are courses related to the arts, economics, law, sports, and culture. *Science* includes mathematics, natural sciences, agriculture, forestry, engineering, and engineering. *Medicine* includes human and health sciences and veterinary medicine.

where v_{0i}, u_{0t}, v_{it} and u_{it} represent the four error components. We control for universities with hospitals by including a dummy variable $z_{1,i}$ equal to 1 when the university has a hospital. Medical school costs are notoriously higher among all departments due to higher faculty members' salaries and higher costs associated with training and research (Agasisti and Salerno; 2007).

2.5 Data

Our analysis relies on a panel dataset built by integrating three official data sources. We gathered information on students, graduates, staff, and university characteristics from the Statistical Office of the Ministry of University and Research (USTAT). Data on publications comes from Incites, a tool that utilizes the Web of Science (WoS) database to provide comprehensive bibliometric metrics for assessing research performance. Furthermore, we collected and developed cost-related data from university financial statements. The cost variable is defined as the total annual current expenditure, adjusted for inflation using the Consumer Price Index (FOI) based on household consumption, as provided by the Italian National Statistics Institute. Some institutions are excluded from the analysis due to their highly specialized nature[14], resulting in a sample of 58 universities observed from 2017 to 2021.

Table 2.1 presents the descriptive statistics of the main variables used in the analysis. The average number of enrolled students in Italian public universities is 25,201, with the largest share in Humanities courses, followed by Science and Medicine. Graduates reflect the number of students across disciplinary areas, averaging 4,780. In addition, about 1,052 academic staff members, including full professors, associate professors, and research associates, contribute to an annual research output of about 2,423 publications. Lastly, the average current expenditure between 2017 and 2021 amounts to 190 million euro. Of course, these average numbers mask the wide heterogeneity of the HE system, especially the difference between small and large universities.

Besides analysing the overall system composition, it is worth examining trends in inputs and outputs over time, with a specific focus on changes following the COVID-19 pandemic. Figure 2.2 illustrates the annual percentage changes in key variables (*Students*, *Graduates*, *Academic staff* and *Publications*) compared to the previous year. The values are always positive, indicating a growth trend in all variables over time. The number

[14] Six special schools: (*Scuola Normale Superiore di Pisa; Scuola IMT di Lucca; Scuola Internazionale Superiore di Studi Avanzati di Trieste; Scuola Superiore di Studi Universitari e Perfezionamento Sant'Anna di Pisa; Istituto Universitario di Studi Superiori di Pavia*); two universities for foreign students (*Università per Stranieri di Perugia; Università per Stranieri di Siena*).

Table 2.1: Descriptive statistics (2017 - 2021)

	Var.	Mean	Std. Dev.	Min	Max
Students	(x_1)	25201	(20387)	3575	102879
Students (Humanities)	(x_{1h})	127256	(11022)	246	49763
Students (Science)	(x_{1m})	7547	(8370)	0	41465
Students (Medicine)	(x_{1s})	4928	(4689)	0	22079
Academic staff	(x_2)	1052	(854)	211	3996
Graduates	(x_2)	4780	(4078)	684	19597
Graduates (Humanities)	(x_{2h})	2461	(2239)	50	11705
Graduates (Science)	(x_{2s})	1454	(1897)	0	11219
Graduates (Medicine)	(x_{2m})	885	(859)	0	4048
Publications$_{(t+1)}$	$(y_{2_{t+1}})$	2423	(2199)	46	10908
Total costs (millions)	(C)	190	(156)	33	778

Note: Authors' calculations based on data provided by the Statistical Office of the Italian Ministry of Education, Universities, and Research (USTAT-MIUR), Incites (Web of Science), and information gathered from university financial statements

of publications experienced the most substantial change, with a remarkable increase of (12%) from 2019 to 2020[15]. The growth trend is evident in all variables within our public university subsample and aligns with the latest ANVUR (2023) statistical report on the Italian higher education system. The only difference concerns the number of graduates, which exhibits an increase in our sample from 2020 to 2021, while the entire system shows a decrease of graduates for the same year. This discrepancy is partly due to a methodological difference, as we report the number of graduates based on the calendar year rather than the academic year[16]. It is also important to note that this analysis focuses exclusively on public universities, excluding private and online universities.

As discussed above, Italian universities have experienced a significant increase in public funding. The logical outcome of this influx of financial resources is a corresponding increase in institutional expenses. While we use total costs to model the university cost function in our efficiency analysis, Figure 2.3 displays the annual average cost changes, desegregated by staff, operating, and other costs.

The breakdown provides an indication of how Italian universities have handled the influx of new public funding. *Staff costs* represent the labor costs incurred by universities for their employed personnel. *Operating costs* encompass all expenditures related to the university's core activities, such as student support, scholarships, procurement of laboratory materials, publishing expenses, and allowances for teaching activities. Finally,

[15]The values of this lagged variable represent the growth in the number of documents published in 2021 in comparison to 2020.

[16]It is worth to note that students in Italy may graduate at different times of the year.

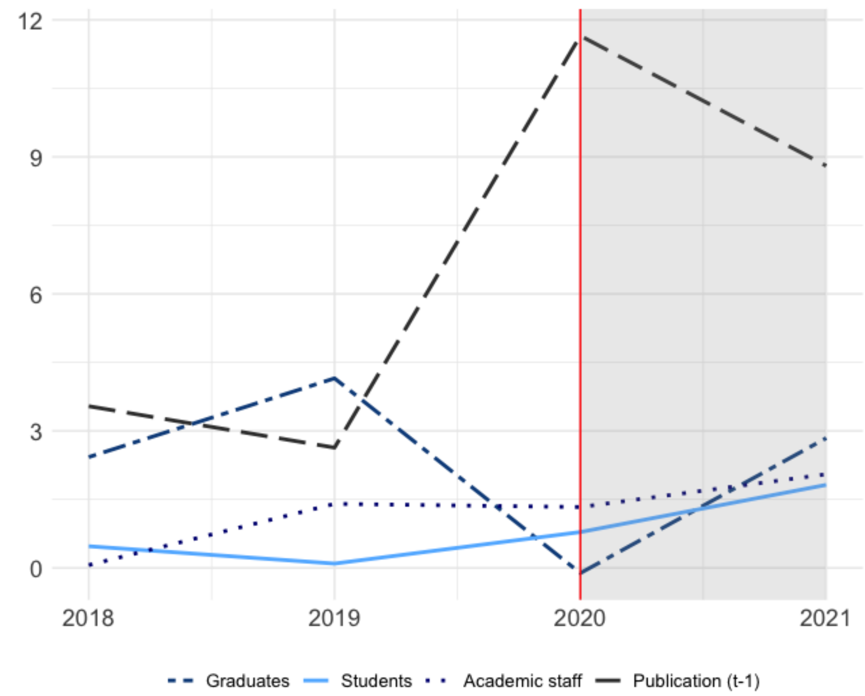


Figure 2.2: Percentage annual change inputs and outputs (2018 - 2021)

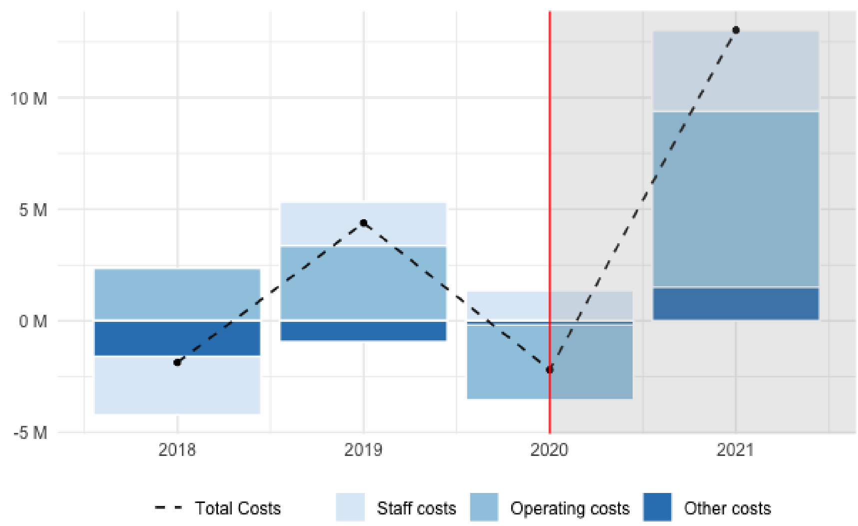


Figure 2.3: Absolute average annual change in costs (2018 - 2021)

Other costs include depreciation, amortization, accruals/use of provisions for risks and charges, and sundry operating charges. The impact of the increase in resources between 2020 and 2021 is evident in operating costs, which increase by more than 10 million on average. Staff costs are less responsive to annual resource changes compared to operating costs. Universities need more time to organize hiring processes and effectively reconfigure teaching and research. However, Staff costs have been rising steadily since 2019, in line with the increasing trend in academic staff shown in Figure 2.2.

2.6 Results

This section reports the results of the efficiency estimations conducted on the sample of 58 Italian public universities observed between 2017 and 2021. We also present some extended results and a robustness analysis concerning the model selection and specification.

2.6.1 Efficiency results

We employ the GTRE stochastic frontier model to estimate both the output distance function and the cost function, from which we derive our efficiency measures. Table A1 and Table A2 in Appendix A report the estimated baseline models. Due to the inclusion of quadratic and interaction terms, the coefficients may not be particularly informative. Moreover, even though it would be possible to estimate marginal and average unit costs, the analysis of output elasticity and scale effects is beyond the scope of this study.

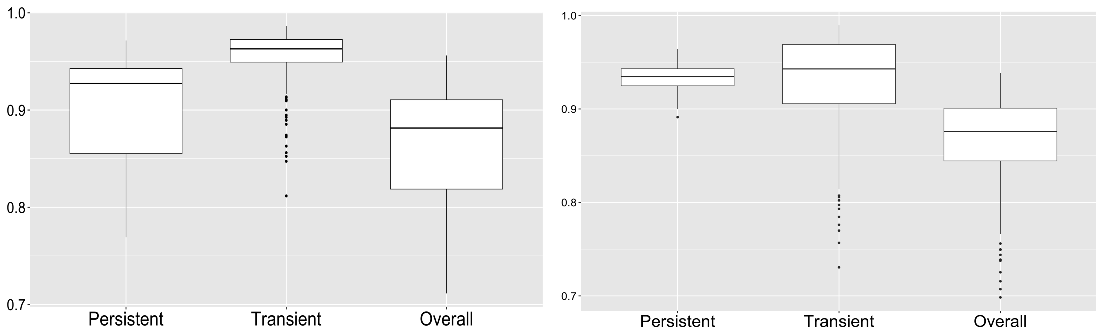
Table 2.2 provides summary statistics of the efficiency values over the 5-year sample. The overall mean efficiency is about 86% for both the production and cost models. Nevertheless, the differences between the production and the cost approach become clear when analysing the persistent and transient components in the two models. The production transient efficiency stands at 95%, which is higher than the average value of the persistent term (90%). In contrast, cost efficiency is 93% for both transient and persistent terms. This finding suggests that inefficiency may come from different sources, and analysing the university production process from different perspectives may reveal these differences.

Table 2.2: Summary statistics - Production and cost efficiency (Model A1 - Model B1)

	Production Efficiency				Cost Efficiency			
	Mean	s.d.	Min	Max	Mean	s.d.	Min	Max
Persistent efficiency	0.902	0.058	0.769	0.971	0.933	0.015	0.891	0.964
Transient efficiency	0.956	0.025	0.812	0.986	0.931	0.050	0.731	0.989
Overall efficiency	0.863	0.059	0.711	0.956	0.867	0.046	0.698	0.939

Figure 2.4 shows the box plots of production (panel a) and cost efficiencies (panel b)

for the entire period. The differences between production and cost efficiency estimates become more evident by analysing the box plots. Notably, persistent efficiency in the production model displays a considerable degree of variability, while, in the cost model, the persistent term exhibits a much smaller standard deviation. Transient inefficiency behaves in a mirror fashion. This result suggests that many universities could implement managerial strategies to reduce cost inefficiency, saving on current expenditures. Conversely, the production side appears characterized by longer-term adjustment dynamics (which deal with an expansion of output's volume), making managerial interventions less feasible.



(a) Production Efficiency **(b)** Cost Efficiency

Figure 2.4: Box Plot - Persistent, Transient and Overall Efficiency (Production and Cost models)

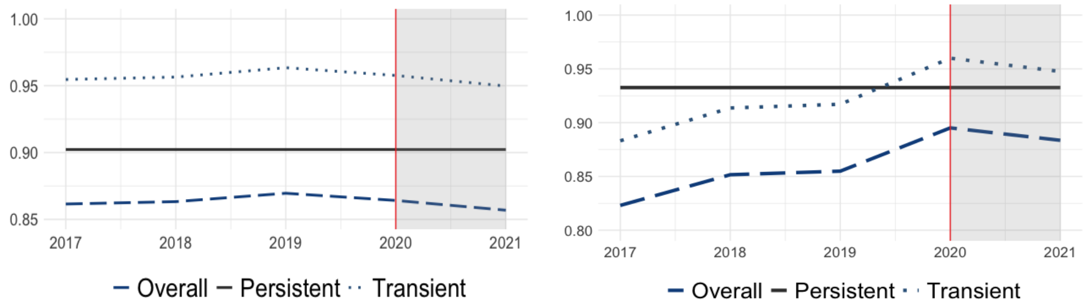
Turning to the change in efficiency over the years, Table 2.3 shows the coefficients associated with the time dummies used to model the transient inefficiency component and test whether the change from 2020 is statistically significant.

Table 2.3: Transient inefficiency: difference between years and geographic areas

	Production Model		Cost Model	
(*2020 excluded*)				
2017	0.305	(0.456)	2.926***	(0.481)
2018	0.186	(0.408)	2.446***	(0.453)
2019	−0.256	(0.370)	2.380***	(0.442)
2021	0.474	(0.333)	0.912**	(0.390)
(*Northwest excluded*)				
Northeast			−0.402	(0.450)
Central			1.054**	(0.440)
Southern			2.534***	(0.414)

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

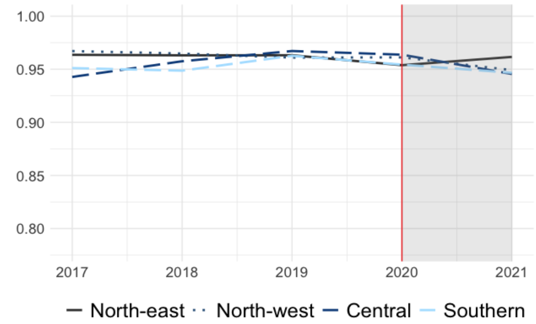
The sign of the coefficients indicates the relationship between the dummies and the inefficiency: a parameter with a positive sign means that the inefficiency is higher, indicating a lower university performance. In the production model, all coefficients are not significant, meaning that Italian public universities' performance has not changed compared to 2020. In contrast, in the cost model, all coefficients are positive and statistically significant compared to 2020. The post-COVID-19 pandemic year is marked by a statistically significant decrease in cost efficiency. Figure 2.5 clearly shows these two results.



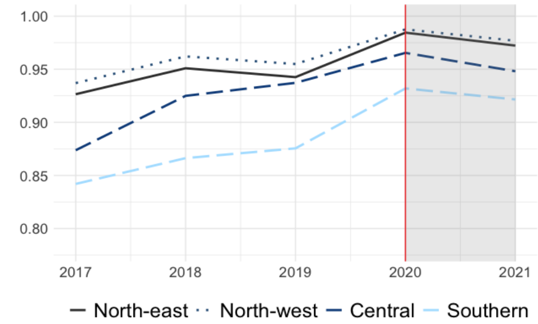
(a) Production Efficiency **(b)** Cost Efficiency

Figure 2.5: Mean Transient Efficiency (2017 - 2021)

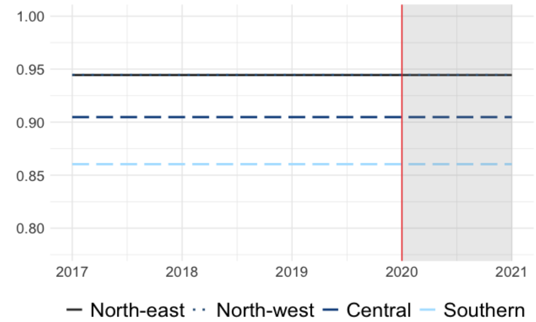
As extensively documented in the literature, Italian public universities exhibit a notable efficiency gap between institutions in different geographical regions. In particular, universities in northern Italy outperform institutions located in other regions (Agasisti and Dal Bianco; 2006; Laureti et al.; 2014; Barra et al.; 2018). We introduce regional dummy variables to model the transient inefficiency term, accounting for the regional gaps. As depicted in Table 2.3, our results reveal statistically significant variations in inefficiency across different geographic areas when assessing cost efficiency. Northern part of the country exhibits the lowest inefficiency, in line with the existing literature. Contrastingly, such disparities do not emerge in the production model. Note that the production model omits regional dummy variables since their inclusion create computational problems in the estimation. The issue in estimation likely stems from the limited variability observed across regions, as illustrated in Figure 2.6 (panel a). In line with the latest studies that indicate a convergence process among Italian universities in terms of productive efficiency (Guccio et al.; 2016), our results complement those of Badunenko and Coppeta (2023), which show that in recent years, geographical differences are mainly explained by the persistent inefficiency term. As illustrated in Figure 2.6, the gaps in overall efficiency (panel e) are attributable to persistent inefficiency (panel c). The results are different when considering the cost model, where the geographic disparities arise from



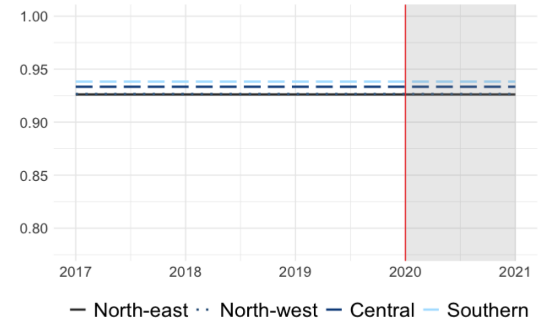
(a) Production - Transient Efficiency



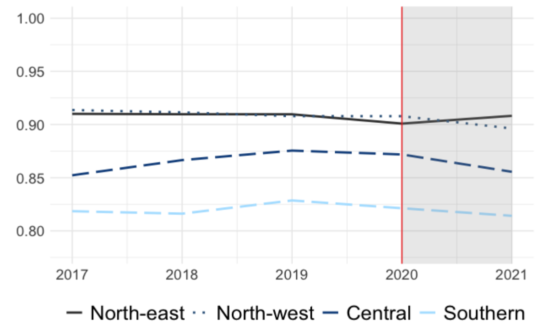
(b) Cost - Transient Efficiency



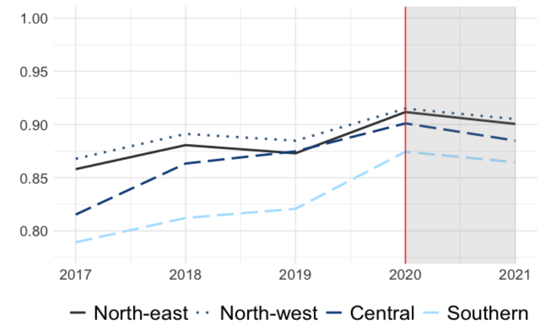
(c) Production - Persistent Efficiency



(d) Cost - Persistent Efficiency



(e) Production - Overall Efficiency



(f) Cost - Overall Efficiency

Figure 2.6: Mean Efficiency by Geographic Area (Production and cost models)

the observation of transient inefficiency in a short-term dynamic. In addition, Figure 2.6 shows that the decreasing effect of cost efficiency in the post-pandemic COVID-19 period is roughly the same in all geographic areas, suggesting that the influx of resources into the system had a homogeneous short-term effect among institutions. However, a possible positive impact in the long term may be uneven. Although the change in efficiency from 2020 is not significant, panel a of Figure 2.6 shows a downward trend for the Northwest, Central, and Southern regions, while the Northeast region shows slight growth. These findings offer insight into potential long-term uneven effects that can be revealed through further analysis spanning additional years.

2.6.2 Robustness and extended analysis

Adequacy of the GTRE Model

Many SF models have been proposed and applied in the literature in recent years. In panel data settings, these models may vary in terms of assumptions about the temporal behavior of inefficiency and the inclusion of a heterogeneity term. The GTRE model employed in the primary analysis is the most general SF model, enabling the decomposition of the error into noise, unobservable individual effects (heterogeneity), and persistent and transient inefficiencies. A preliminary robustness analysis underpins the decision to opt for the GTRE model. We begin by estimating a simple model with only time-varying inefficiency, progressively adding error components. The performance of the model is then assessed using the LR test. Table 2.4 presents the coefficients of the error terms (Random effects, Transient inefficiency, and Persistent inefficiency), along with the LR test results for the estimated models.

Table 2.4: Comparison of SF panel models (Production Models)

	P1		P2		P3		P4	
Transient inefficiency	-3.629***	(0.148)	-5.637***	(0.274)	-5.729***	(0.266)	-5.717***	(0.260)
Persistent inefficiency			-3.548***	(0.280)			-5.060***	(0.171)
Random effects					-7.299***	(0.370)	-7.294***	(0.367)
$\log L$	264.25		406.11		404.54		405.25	
LR test	282		- 1.72		1.42			

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$. LR test= $-2(\log L - \log L_{GTRE})$.

Table 2.5: Comparison of SF panel models (Cost Models)

	C1		C2		C3		C4	
Transient inefficiency	-12.38	(130.9)	-14.70	(342.5)	-3.687***	(0.117)	-3.651***	(0.107)
Persistent inefficiency			-2.663***	(0.261)			-5.211***	(0.133)
Random effects					-3.277***	(0.149)	-3.197***	(0.087)
$\log L$	132.36		193.56		201.03		203.50	
LR test	142		21.28		4.94			

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$. LR test = $-2(\log L - \log L_{GTRE})$.

P1 is the simplest model where only transient inefficiency is estimated. P2 does not account for heterogeneity and excludes the random effects, while P3 does not include persistent inefficiency. Finally, P4 corresponds to the GTRE model, where all error terms are estimated. The critical values of the mixed χ^2 distribution are 5.412 and 2.705 for significance levels of 0.01 and 0.05, respectively, with 1 degree of freedom. For 2 degrees of freedom, the corresponding critical values are 8.273 and 5.138[17]. The same analysis is conducted for the cost models (C1, C2, C3, and C4), and the results are presented in Table 2.5. At the 1% significance level, models P1 and C1 are consistently rejected in all comparisons. In the context of the production model, the hypothesis of zero variance in persistent inefficiency cannot be rejected at the 5% significance level. Nevertheless, we opt to retain this specification, as all error terms are significant, and the transient inefficiency term remains uninfluenced by the presence of the inefficiency term. Furthermore, according to Table 2.5, the GTRE specification is always preferred for cost models, at least at a 5% significance level. An additional interesting finding is that transient inefficiency is significant only in models C3 and C4, highlighting the critical importance of accounting for individual effect heterogeneity in estimating cost efficiency.

Publication lag, Subject mix and Inflation

As an additional robustness check on the evidence indicating a decrease in cost efficiency after the COVID-19 pandemic, we performed multiple analyses by examining different model specifications. The estimation results for four different cost model specifications are presented in Table S1 to S5 in the Appendix 2.B.

The initial check focuses on the lag in research output. To account for the time delay between research activity and publication, we use the number of publications at year $t+1$ in our baseline model. We repeat the estimates using the number of publications at year t (M1). Specifications M2 and M3 address the issue of subject mix. In M2, rather than distinguishing based on teaching output as in the baseline model, we use the number of publications categorized by subject mix, including humanities, sciences, and medicine. M3 represents a simplified cost model where publications and graduates are aggregated at the university level without differentiation by subject. Lastly, M4 represents a model in which costs are not adjusted for inflation. Figure 2.7 shows the average transient efficiency of the four different specifications over time.

Although the models are not directly comparable, the figure provides a qualitative indication of the robustness of the result. In all specifications, the efficiency increases until 2020 and then decreases in the year after the pandemic. In addition, it should be noted that M4, which does not take inflation into account, shows the most pronounced effect of decreasing cost inefficiency. The cost model without inflation adjustment shows a higher

[17]See (Kodde and Palm; 1986) for the critical values of the mixed χ^2 distribution

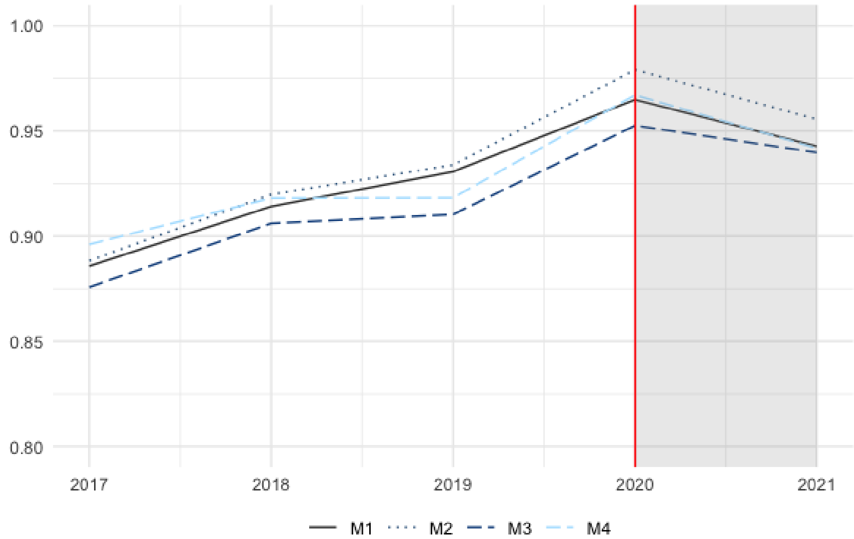


Figure 2.7: Robustness - Transient efficiency (M1- M4)

magnitude and significance of the 2021 time dummy, as depicted in Table S5. Despite the analysis only partially capturing the period of increasing inflation that manifested in years after the COVID-19 pandemic, these preliminary findings suggest its relevance in explaining the expenditure behavior of Italian universities.

2.7 Discussion and concluding remarks

In response to the significant disruption caused by the COVID-19 pandemic, many European countries have implemented measures to support universities through by increasing public funding. In this context, the analysis of the Italian HE system is of broad interest. First, due to the severity of the pandemic compared to its European counterparts, Italy received a very high level of public financial support. Second, the country has experienced one of the lengthiest school closures in the world (UNESCO; 2020), exposing the HE system to significant risks associated with the adverse effects of the COVID-19 pandemic.

This paper analyzes the production and cost efficiency of 59 Italian public universities between 2017 and 2021 using a Generalized True Random Effect (GTRE) stochastic frontier model. By specifying heteroskedasticity in the inefficiency term, we examine whether the policies implemented in response to the COVID-19 pandemic is associated with a change in the efficiency of Italian public universities. Additionally, we explore the heterogeneity of policy effects by analysing the disparities in efficiency among Italian regions.

Our results reveal a reversal of the positive trend in efficiency highlighted in the literature in recent years (Agasisti; 2016; Guccio et al.; 2016; Agasisti et al.; 2016). Specifically, we observe cost efficiency loss after the COVID-19 outbreak. At the same time, our analysis using an output distance function model shows that the production efficiency has exhibited stability, with no significant change compared to pre-pandemic levels. University managers and policymakers should be aware that the analysis of costs and production efficiency may yield distinct results and capture different aspects of the complex production process of universities. More closely, we observe higher variance in the performance of universities when analysing short-term cost inefficiency (transient cost inefficiency) compared to the production model (transient production inefficiency), where universities cluster more closely around the average. These results suggest that universities are more responsive to cost changes, highlighting the significant role that resource allocation may have on university efficiency. Finally, it is relevant to note that although the cost model shows the expected efficiency gap among Italian universities, COVID-19 has affected all universities homogeneously, as efficiency decreases without significant differences between geographic areas. Understanding if the decline in efficiency is only the effect of COVID-19 (or other factors were at play) remains an open issue.

Although the loss of cost efficiency represents a negative outcome for the public finances, we emphasize that policy objectives can vary significantly based on the contextual factors driving their implementation. During the economic crisis, reforms in the European HE systems, driven by budget constraints and austerity measures, aimed to enhance university efficiency (Martínez-Campillo and Fernández-Santos; 2020). Conversely, during the COVID-19 emergency context, the primary goal shifted to ensuring the continuity of teaching and research activities, minimising learning and knowledge losses rather than improving efficiency. Beyond policy goals, however, this issue raises the broader question of how universities respond to changes in funding. Organizations that receive public funds, such as universities, could easily engage in behavior aimed at spending all the income at their disposal (Johnes; 2020), potentially leading to highly inefficient productive activity. However, the recent marketization of the higher education sector with the gradual introduction of performance-based funding mechanisms has led to a quasi-market structure that increases competition among universities (Teixeira et al.; 2006; Agasisti and Catalano; 2006). In this setting, universities are likely to engage in optimization behavior consistent with cost-minimising strategies. In the Italian case, we observe a gradual increase in public resources allocated to public universities from 2017 onwards, reversing the path of significant reduction up to 2013 and stability up to 2016 (ANVUR; 2023). However, this increase does not appear to have affected the efficiency of universities until the outbreak of the COVID-19 pandemic. We might speculate that the gradually rise in public funding occurred within a conventional framework of well-established resource allocation mechanisms driven primarily by incentive-based mechanisms. Instead, the influx of a significant amount of resources, as has been the case since 2020, may have led to a breakdown in established allocation mechanisms, leading universities to consume all the injected resources regardless of financial sustainability and efficiency. A comprehensive understanding of the effects of this influx of public resources will be only achievable through further research, analysing universities' behavior over additional years of observation. In the upcoming years, productive efficiency may exhibit growing heterogeneity in university performance. Some universities may be able to use the increased resources effectively, leading to an increase in efficiency. Conversely, others may waste resources through suboptimal management decisions.

Some shortcomings of this study are related to the challenge of accounting for quality. While the literature on university efficiency emphasizes the importance of including quality in efficiency measurement, it is well known that identifying appropriate quality indicators to describe higher education processes is a complex task (Agasisti and Pérez-Esparrells; 2010). Furthermore, the unique circumstances arising from the COVID-19 pandemic introduce additional complexity to quality measurement. Variables used in the literature to capture quality, such as GPA and credits earned by students, were directly influenced by COVID-19 (Rodríguez-Planas; 2022). In addition, assessing the quality of research through citations is constrained by the relatively short period since publication. Analyzing the the effects of COVID-19 on efficiency, it could be concluded that Italian universities, due to increased resources, may have mitigated the potential drawbacks of closures, ensuring a constant level of production efficiency and guaranteeing continuity of teaching and research activities, albeit at higher costs in the short term. However, it might be the case that, in addition heightened university expenditures, the constant production efficiency has come at the cost of diminished quality, yielding negative implications for both human capital and scientific knowledge.

In future research, it is crucial to focus on quality metrics to gain a more comprehensive understanding of the pandemic effects in higher education sector. More work is also needed to assess how higher education systems respond to Covid-19 pandemic across different countries and whether increased financial resources contribute to long-term efficiency gains.

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2.A Appendix A: Production and Cost Model Tables

Table A1: Output distance function: estimates of coefficients

	Production Model	
University production function		
Intercept	7.001***	(0.190)
log(x1)	−2.577***	(0.039)
log(x2)	0.662***	(0.048)
log(y2/y1)	0.355**	(0.152)
0.5 * $\log(x1)^2$	0.175***	(0.012)
0.5 * $\log(x2_{t+1})^2$	−0.173***	(0.011)
0.5 * $\log(y2_{t+1}/y1)^2$	0.020	(0.030)
t	−0.027***	(0.003)
log(x1):log(x2)	0.020***	(0.007)
log(x1):log($y2_{t+1}$/y1)	−0.127***	(0.022)
log(x2):log($y2_{t+1}$/y1)	0.184***	(0.044)
1. Random effects component: $\log \sigma^2_{v_{0i}}$		
Intercept	−5.552***	(0.181)
2. Persistent inefficiency component: $\log \sigma^2_{u_{0i}}$		
Intercept	−4.077***	(0.147)
3. Random noise component: $\log \sigma^2_{v_{it}}$		
Intercept	−7.289***	(0.354)
4. Transient inefficiency component: $\log \sigma^2_{u_{it}}$		
Intercept	−5.917***	(0.389)
(2020 excluded)		
2017	0.305	(0.456)
2018	0.186	(0.408)
2020	−0.256	(0.370)
2021	0.474	(0.333)
Sample Characteristics		
N	58	
$\sum_{i=1}^{N} T_i$	290	
Sim. logL	408.92	

Note: Standard errors in parentheses; * $p < .10$, ** $p < .05$, *** $p < .01$.

Table A2: Cost function: estimates of coefficients

	Cost Model	
University cost function		
Intercept	16.001***	(0.091)
log(y1h)	0.064**	(0.034)
log(y1s)	−0.189***	(0.058)
log(y1m)	0.058***	(0.028)
log($y2_{t+1}$)	0.0537	(0.058)
0.5 * log(y1h)^2	0.061***	(0.007)
0.5 * log(y1s)^2	0.020	(0.018)
0.5 * log(y1m)^2	0.037***	(0.007)
0.5 * log($y2_{t+1}$)^2	0.068***	(0.015)
log(y1h):log(y1s)	0.010	(0.010)
log(y1h):log(y1m)	−0.008	(0.011)
log(y1h):log($y2_{t+1}$)	−0.053***	(0.011)
log(y1s):log(y1m)	−0.016**	(0.007)
log(y1s):log($y2_{t+1}$)	0.019**	(0.009)
log(y1m):log($y2_{t+1}$)	−0.001	(0.010)
Hospital	0.280***	(0.027)
1. Random effects component: $\log \sigma^2_{v_{0i}}$		
Intercept	−3.323***	(0.051)
2. Persistent inefficiency component: $\log \sigma^2_{u_{0i}}$		
Intercept	−4.914***	(0.154)
3. Random noise component: $\log \sigma^2_{v_{it}}$		
Intercept	−7.533***	(0.442)
4. Transient inefficiency component: $\log \sigma^2_{u_{it}}$		
Intercept	−7.865***	(0.649)
(*2020 excluded*)		
2017	2.926***	(0.481)
2018	2.446***	(0.453)
2019	2.380***	(0.442)
2021	0.912**	(0.390)
(*Northwest excluded*)		
Northeast	−0.402	(0.450)
Central	1.054**	(0.440)
Southern	2.534***	(0.414)
Sample Characteristics		
N	58	
$\sum_{i=1}^{N} T_i$	290	
Sim. logL	278.42	

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

2.B Appendix B: Robustness Tables

Table S1: Robusntess - Model M1: Number of publications at year t

	M1	
University cost function		
Intercept	15.31***	(0.105)
log(x1h)	0.299***	(0.023)
log(y1s)	−0.154***	(0.026)
log(y1m)	0.177***	(0.018)
log(y2)	−0.071	(0.053)
0.5 * log(y1h)^2	0.036***	(0.009)
0.5 * log(y1s)^2	0.032***	(0.010)
0.5 * log(y1m)^2	0.042***	(0.008)
0.5 * log(y2)	0.1344***	(0.011)
log(y1h):log(y1s)	−0.017**	(0.007)
log(y1h):log(y1m)	−0.002	(0.007)
log(y1h):log(y2)	−0.068***	(0.006)
log(y1s):log(y1m)	−0.012**	(0.006)
log(y1s):log($y2_{t+1}$)	0.001	(0.004)
log(y1m):log($y2_{t+1}$)	−0.031***	(0.010)
Hospital	0.346***	(0.028)
1. Random effects component: $\log \sigma^2_{v_{0i}}$		
Intercept	−2.851***	(0.065)
2. Persistent inefficiency component: $\log \sigma^2_{u_{0i}}$		
Intercept	−5.325***	(0.594)
3. Random noise component: $\log \sigma^2_{v_{it}}$		
Intercept	−7.199***	(0.309)
4. Transient inefficiency component: $\log \sigma^2_{u_{it}}$		
Intercept	−8.248***	(0.702)
Sample Characteristics		
N	58	
$\sum_{i=1}^{N} T_i$	290	
Sim. logL	269.62	

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

Table S2: Robusntess - Model M2: Publications disaggregated by subject

	M2	
University cost function		
Intercept	19.62***	(0.464)
log(y1)	−1.104***	(0.0674)
log(y2h$_{t+1}$)	0.254	(0.173)
log(y2s$_{t+1}$)	−0.402	(0.262)
log(y2m$_{t+1}$)	0.439***	(0.042)
0.5 * log(y1)^2	0.216***	(0.027)
0.5 * log(y2h$_{t+1}$) ^{2}	0.1194**	(0.057)
0.5 * log(y2s$_{t+1}$) ^{2}	−0.0761**	(0.037)
0.5 * log(y2m$_{t+1}$)	0.003	(0.015)
log(y1):log(y2h)	−0.093	(0.084)
log(y1):log(y2s)	0.102***	(0.035)
log(y1):log(y2m)	−0.077***	(0.016)
log(y2h):log(y2s)	0.002	(0.006)
log(y2h):log(y2m)	−0.022	(0.004)
log(y2s):log(y2m)	0.046***	(0.010)
Hospital	0.487***	(0.069)
1. Random effects component: $\log \sigma^2_{v_{0i}}$		
Intercept	−3.472***	(0.240)
2. Persistent inefficiency component: $\log \sigma^2_{u_{0i}}$		
Intercept	−2.889***	(0.174)
3. Random noise component: $\log \sigma^2_{v_{it}}$		
Intercept	−7.109***	(0.252)
4. Transient inefficiency component: $\log \sigma^2_{u_{it}}$		
Intercept	−9.447***	(0.870)
Sample Characteristics		
N	58	
$\sum_{i=1}^{N} T_i$	290	
Sim. logL	280.88	

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

Table S3: Robusntess - Model M3: Robusntess - Model M3: Publications and graduates are aggregated at the university level

	M3	
University cost function		
Intercept	18.978^{***}	(0.110)
log(y1)	-0.785^{***}	(0.067)
log($y2_{t+1}$)	-0.010	(0.015)
0.5 * log(y1)^2	0.152^{***}	(0.006)
0.5 * log($y2_{t+1}$)^2	0.048^{***}	(0.007)
log(y1):log($y2_{t+1}$)	-0.008^{*}	(0.005)
Hospital	0.363^{***}	(0.025)
1. Random effects component: $\log\sigma^2_{v_{0i}}$		
Intercept	-2.988^{***}	(0.070)
2. Persistent inefficiency component: $\log\sigma^2_{u_{0i}}$		
Intercept	-4.816^{***}	(0.319)
3. Random noise component: $\log\sigma^2_{v_{it}}$		
Intercept	-8.007^{***}	(0.662)
4. Transient inefficiency component: $\log\sigma^2_{u_{it}}$		
Intercept	-7.523^{***}	(0.5529)
Sample Characteristics		
N	58	
$\sum_{i=1}^{N} T_i$	290	
Sim. logL	277.51	

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

Table S4: Robusntess - Model M4: Costs not adjusted for inflation

	M4	
University cost function		
Intercept	15.1935***	(0.1396)
log(y1h)	0.1147***	(0.0351)
log(y1s)	−0.1055***	(0.0319)
log(y1m)	0.0670***	(0.0130)
log(y2$_{t+1}$)	0.1177*	(0.0491)
0.5 * log(y1h)^2	0.0751***	(0.0071)
0.5 * log(y1s)^2	0.0229	(0.0163)
0.5 * log(y1m)^2	0.0507**	(0.0213)
0.5 * log(y2$_{t+1}$)^2	0.068***	(0.015)
log(y1h):log(y1s)	−0.0071	(0.0173)
log(y1h):log(y1m)	−0.0169***	(0.0079)
log(y1h):log(y2$_{t+1}$)	−0.0520***	(0.0095)
log(y1s):log(y1m)	−0.0170**	(0.0067)
log(y1s):log(y2$_{t+1}$)	0.0308***	(0.0111)
log(y1m):log(y2$_{t+1}$)	0.0008	(0.0105)
Hospital	0.2878***	(0.0423)
1. Random effects component: $\log\sigma^2_{v_{0i}}$		
Intercept	−3.1098***	(0.1127)
2. Persistent inefficiency component: $\log\sigma^2_{u_{0i}}$		
Intercept	−5.1968***	(0.3774)
3. Random noise component: $\log\sigma^2_{v_{it}}$		
Intercept	−7.2900***	(0.3474)
4. Transient inefficiency component: $\log\sigma^2_{u_{it}}$		
Intercept	−8.2376***	(0.6339)
Sample Characteristics		
N	58	
$\sum_{i=1}^{N} T_i$	290	
Sim. logL	279.49	

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

Table S5: Robustness - (M1 - M4) Transient inefficiency: difference between years and geographic areas

	M1		M2		M3		M4	
(2021 excluded)								
2017	3.146***	(0.533)	4.033***	(0.695)	2.682***	(0.403)	3.084***	(0.510)
2018	2.697***	(0.504)	3.619***	(0.694)	2.291***	(0.387)	2.717***	(0.505)
2019	2.308***	(0.492)	3.276***	(0.672)	2.219***	(0.384)	2.731***	(0.493)
2021	1.285***	(0.459)	1.840***	(0.578)	0.869***	(0.339)	1.708***	(0.444)
(Northwest excluded)								
Northeast	-0.287	(0.529)	-0.149	(0.706)	-0.050	(0.415)	-0.4483	(0.584)
Central	1.015**	(0.479)	1.513**	(0.619)	1.201**	(0.391)	0.9190**	(0.464)
Southern	2.799***	(0.437)	3.039***	(0.483)	2.341***	(0.376)	2.5809***	(0.431)

Note: Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

Chapter 3

Long-Term Efficiency in Higher Education: A Comparative Study of European Public Universities*

Abstract
This study explores the efficiency of Higher Education Institutions in a multi-country perspective. Our analysis is based on a sample of 239 public universities from 10 European countries between 2011 and 2019. Using a four-component stochastic frontier model, we disentangle the efficiency into persistent (long-run) and transient (short-run) components, investigating the impact of funding allocation mechanisms on universities' performance. Results reveal significant heterogeneity in efficiency scores both across and within countries. Differences between countries appear to be driven primarily by long-term inefficiency, highlighting the importance of structural factors in explaining performance levels within the sector. Further, a high share of tuition fees and third-party funding correlates with better performance. The results highlight the central role of national authorities and governments in shaping the regulatory environment and financial incentives.

3.1 Introduction

Higher Education Institutions (HEIs) play a central role in the economic development of countries by promoting human capital and fostering innovation through knowledge creation (Hanushek; 2016). As part of Europe's post-pandemic recovery strategy, the European Union recognizes high-quality HEIs as a prerequisite for fostering open, democratic, equitable, and sustainable societies promoting sustainable growth, entrepreneurship, and employment (European Commission; 2022). From a policy perspective, it is crucial to guarantee sufficient investment for enhancing education and research outcomes while ensuring that universities perform optimally, guaranteeing effective, fair, and efficient use of public resources. In this context, analyzing the efficiency of European higher education systems is crucial for identifying policy levers that can influence the behavior of universities, steering them towards enhanced performance.

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A growing body of literature on university efficiency examines differences among institutions within the same higher education system (Witte and López-Torres; 2017). Although country-specific studies provide valuable insights into the situations of their respective systems, formulating definitive and general conclusions about the overall efficiency of universities remains challenging (Agasisti; 2023). In this vein, some works have adopted a supranational perspective by comparing higher education systems between two countries (Agasisti and Johnes; 2009; Agasisti and Pérez-Esparrells; 2010; Agasisti and Gralka; 2019; Agasisti and Berbegal-Mirabent; 2021). The focus on pairs of countries is mainly due to the lack of homogeneous and comparable micro-data. However, the recent establishment of the European Tertiary Education Register (ETER)[1], a unified database on European higher education institutions, has opened up a new strand of literature with a broader geographical scope, allowing comparisons among countries at the European level. In this direction, Bonaccorsi et al. (2007) analyzed economies of scale and specialization in European universities in Italy, Spain, Portugal, Norway, Switzerland, and the UK. Focusing on the same topic, Daraio et al. (2015) examined 400 HEIs from 16 European countries in the 2008/2009 academic year. Subsequently, expanding the number of institutions involved to 944, Veiderpass and McKelvey (2016) measured efficiency for the same year. Breaking new ground, Wolszczak-Derlacz (2017) extended the analysis to 500 universities spanning 10 European countries and the US, measuring efficiency beyond Europe and comparing various European and American HEIs for the first time. Daraio et al. (2021) shifted the focus towards latent heterogeneity in university efficiency, analyzing institutions in 16 countries during the academic year 2011/2012. Finally, (Herberholz and Wigger; 2021) investigates the relative efficiency of 450 European universities between 2011 and 2014, focusing on subject orientation. These studies primarily focus on short-term efficiency, whether by analyzing factors influencing managerial efficiency, testing for economies of scale and scope, or examining heterogeneity across institutions.

In this paper, we extend the analysis to a long-run perspective by measuring the efficiency of 239 European higher education institutions across 10 countries (Austria, Switzerland, Germany, Ireland, Lithuania, the Netherlands, Norway, Portugal, Sweden, and the UK) from 2011 to 2019. Through the use of the Generalized True Random Effect (GTRE) Stochastic Frontier (SF) model, we can disentangle inefficiency into persistent (long-term) and transient (short-term) components while accounting for unobservable university heterogeneity (Colombi et al.; 2014). To the best of our knowledge, this is

[1] The ETER database is the outcome of a project funded by the European Commission. Some cited empirical analyses also utilize previous versions of the ETER database (Aquameth and Eumedia).

the only study that compares the performance of European institutions over such an extended period, with a specific focus on long-term persistent inefficiency.

Regarding the factors that impact HEIs' ability to achieve high levels of performance, existing literature suggests that, alongside management practices (Avkiran; 2001) and environmental factors (Agasisti et al.; 2023), the incentive structure enforced by the funding system plays a significant role (Bolli et al.; 2016; Agasisti and Berbegal-Mirabent; 2021). Public universities are considered complex organizations that respond to incentives aligned with their objectives of maximizing available funds and institutional reputation (Rey; 2001; Beath et al.; 2005). In this view, national authorities and agencies can affect institutional performance through incentive schemes linked to funding mechanisms. Institutions respond to funding policies by prioritizing specific activities rewarded by funding schemes (Hicks; 2012). The level, composition, and mechanisms of university funding are all part of a broader spectrum of governance arrangements (Jongbloed and Vossensteyn; 2016).

After the reforms of European higher education systems began in the late 1990s, the allocation of public resources to HEIs shifted from a historical quota-based model, where institutions received funding regardless of their performance, towards Performance-Based Funding (PBF) models that allocate public resources based on performance evaluations (Jongbloed; 2011). The idea is to create economic incentives for HEIs to motivate them toward higher performance. PBF has become a widespread mechanism used by European higher education systems. However, they differ in the mix between formula-based and negotiation-based systems, the performance indicators and criteria utilized, and the proportions of funding tied to performance (Jongbloed et al.; 2023). The response to the national funding scheme can vary among universities within a country based on initial conditions and environmental university characteristics (Badunenko and Coppeta; 2023); however, the incentives they provide remain consistent across all institutions. It is reasonable to assume that part of the funding scheme translates into performance differences between countries. Furthermore, the extent to which these models are implemented varies widely between countries, with some systems largely still anchored to historical quota-based resource allocation models (Jongbloed et al.; 2023). These differences likely persist over time, resulting in long-term efficiency disparities between countries due to different target schemes and incentives.

As a second policy trend, reforms have introduced cost-sharing mechanisms by increasing or implementing tuition fees. In the context of growing demand for educational services and shrinking public budgets, students share the costs of their educational benefits (Johnstone; 2006). In addition, tuition fees introduce market elements by treating fees as a price that links funding and services provided to students, thereby increasing efficiency and responsiveness (Pruvot and Estermann; 2012). As further competitive funding, revenues from other entities (third-party funding) often entail cost-sharing with private and public external entities. This type of funding mainly consists of resources allocated through projects, assuming that project evaluation mechanisms and competition for resources can improve research performance by facilitating more efficient use of funding resources (Aghion et al.; 2010). Despite various contributions, the literature on the effects of competition for funding on university efficiency remains limited and controversial. Cherchye and Abeele (2005) and Carayol and Matt (2006) provided evidence of a positive relation between third-party funding and efficiency, while finding no impact regarding private funds. However, Bonaccorsi et al. (2006) reported an inverse U-shaped relation between private funding and efficiency. Bolli et al. (2016) provide further insights into the effects of competitive funding, indicating that international public funds decrease the productivity of the best performing universities. At the same time, they also show that competition for international public funds lead to a positive impact on efficiency. Although not directly through funding analysis, a competitive effect also emerges in Abbott and Doucouliagos (2003) and Agasisti (2009), which provide evidence of a positive effect of competition for students in Australia and Italy, respectively.

To explore differences across countries and analyze the effects of various funding schemes on universities efficiency, we adopt the approach suggested by (Badunenko and Kumbhakar; 2017), which introduces determinants of inefficiency via the variance of the inefficiency terms. Specifically, we examine the impact of high share of tuition fess and third party funding on universities' long-term performance. Additionally, we investigate the association between university size and persistent inefficiency.

Our results reveal significant heterogeneity in efficiency scores both across and within countries, with persistent long-run efficiency playing an important role. Further, we find that differences between countries are substantially driven by persistent inefficiencies, suggesting that higher education system and the incentive mechanisms established in each country explain much of the performance differences. Specifically, we found evidence of a positive relationship between the share of third-party funding and tuition fees on long-term efficiency, suggesting that diversification of funding may represent a relevant policy to facilitate efficiency gains.

The rest of the paper is organized as follows. Section 3.2 introduces the methodology employed in the efficiency estimation. Section 3.3 provide information on the European Universities data and details the empirical model. Section 3.4 presents and discusses our main estimation results, while Section 3.5 summarizes and concludes the paper.

3.2 Methodology

To analyze the efficiency of European HEIs and the effect of funding on both persistent (short-run) and transient (long-run) efficiency[2], we rely on the concept of the distance function introduced by (Shepherd; 1970). Universities are considered complex organizations that generate multiple outputs, such as the number of graduates and academic publications, using different inputs, including human, financial, and structural resources (Johnes; 2022). In this setting, the output distance function enables modeling multiple-input, multiple-output production processes through a cardinal representation of technology. Let $P(x)$ be the feasible output set, which contains all output vectors y that can be produced by the input vectors x. We define the output distance function as:

$$D_o(y,x) = \min\left\{\theta \middle| \frac{y}{\theta} \in P(x)\right\}, \tag{3.1}$$

Equation (3.1) shows the potential expansion of each output in y when all the inputs are kept at their levels. The distance function is a function of both outputs and inputs, $D_o(y,x) = f(y,x,\beta)$, where β is the technology parameter vector to be estimated. The distance function is non-decreasing in output, homogeneous of degree 1 in y and decreasing in x [3]. By linear homogeneity restrictions, the outputs can be normalized by an arbitrary output variable, for example, y_1, viz.,

$$y_1^{-1} D_o(x,y) = f(x,\tilde{y}), \tag{3.2}$$

where $\tilde{y} = \left(\frac{y_2}{y_1}, ..., \frac{y_M}{y_1}\right)$. Setting $e^{-u} = D_o(y,x)$, where $u \geq 0$, taking the logs of both sides of (3.2) and rearranging terms, we obtain

$$-\log y_1 = \log f(x,\tilde{y}) + u + v \tag{3.3}$$

where u is taken as a measure of inefficiency indicating quantifies the maximum rate of increase in output while using the same quantity of inputs.

The empirical estimation follows a parametric Stochastic Frontier (SF) approach. Over the past decades, numerous SF models have been proposed in the literature to exploit the panel nature of the data. These models vary in terms of the temporal behavior of inefficiency (which may be persistent or invariant), the interpretation of unobservable

[2]Throughout the paper, we use the terms "persistent efficiency" and "long-run efficiency" as well as "transient efficiency" and "short-run efficiency" interchangeably.

[3]These properties derive directly from the axioms on the technology set. For further details, refer to Färe and Primont (1995).

individual heterogeneity, and the estimation techniques.[4]. The natural extension of the standard SF model to the panel data setting can be expressed as follows:

$$-\log y_{1,it} = \log f(x_{it}, \tilde{y}_{it}) + u_{it} + v_{it}. \tag{3.4}$$

where university $i = 1, ..., n$ is observed in period $t = 1, ...T_i$, v_{it} is the noise term and $u_{it} \geq 0$ is time-varing technical inefficiency. Although this model allows the estimation of time-varying inefficiency, it completely ignores heterogeneity. Extending the model to include a heterogeneity term has led to various formulations of the panel SF model with different interpretations of the term. Some scholars consider it to represent persistent (long-run) inefficiency (e.g., Kumbhakar and Heshmati (1995)). Others interpret the invariant component as unobservable firm heterogeneity unrelated to inefficiency (e.g., Greene (2005)). However, confounding effects can affect the results of both types of models.

The four-component SF model, also known as the Generalized True Random Effect (GTRE) model (Kumbhakar et al.; 2014; Colombi et al.; 2014; Tsionas and Kumbhakar; 2014), recently introduced the possibility of disentangling persistent inefficiency from unobservable individual heterogeneity. Two time-invariant components capture firms' latent heterogeneity and persistent (long-run) inefficiency. The other two components are observation-specific, varying across firms and over time. They capture transient (short-run) inefficiency and random noise. Formally, we can express the GTRE model as:

$$-\log y_{1,it} = \log f(x_{it}, \tilde{y}_{it}) + u_{0i} + u_{it} + v_{0i} + v_{it}, \tag{3.5}$$

where u_{it} and u_{0i} represent transient and persistent inefficiency, respectively, v_{0i} capture the unobserved university heterogeneity and v_{it} is the classical symmetric error term. Note that the overall inefficiency is the sum of persistent and transient inefficiency $u = u_{0i} + u_{it}$; and the overall efficiency correspond to the product of persistent and transient efficiencies,

$$e^{-u} = e^{-u_{0i}} \times e^{-u_{it}}. \tag{3.6}$$

While the random noise and the random effects are assumed to be normally distributed, the persistent and inefficiency terms are assumed to be half-normally distributed. Following Badunenko and Kumbhakar (2017), we introduce the determinants of inefficiency by specifying heteroskedastic inefficiency terms. Starting with the persistent term, we let the pre-truncated variance of u_{oi} depend on a vector time-invariant determinants z_{0i},

[4]See Kumbhakar et al. (2022) for a comprehensive review of existing panel SF models.

viz.,

$$u_{0i} \sim N^{+}\left(0, \sigma^2_{u_{0i}}\right), \quad \sigma^2_{u_{0i}} = \exp\left(z_{0i}\, \eta\right) \tag{3.7}$$

Similarly, for the transient inefficiency term, z_{it} represents the vector of time-varying covariates that determine the short-run inefficiency introduced by the pre-truncated variance of u_{it}:

$$u_{it} \sim N^{+}\left(0, \sigma^2_{u_{it}}\right), \quad \sigma^2_{u_{it}} = \exp\left(z_{ti}\, \omega\right). \tag{3.8}$$

Thus, the determinants of persistent inefficiency are time-invariant, while the determinant of transient inefficiency can vary by university and over time. Finally, η and ω represents the parameter to be estimated.

3.3 Data sample and empirical model

The analysis is based on the European Tertiary Education Register (ETER), enriched with data on publications obtained through SciVal (by Elsevier Publishing). The ETER database is a valuable tool for cross-country analysis of higher education systems, providing detailed microdata on institutional activities and adhering to rigorous data validation and control procedures (Lepori et al.; 2023). Nevertheless, HEIs exhibit considerable heterogeneity in terms of institutional mandates, missions, mix of activities, legal status, and institutional governance (Lepori; 2022). Failure to adequately account for this heterogeneity can lead to inaccurate results. To increase the comparability of institutions, we restricted our dataset to public and government-dependent universities, aligning with the approach adopted by much of the literature. According to the standardized ETER classification of European HEIs, *"Universities"* are institutions with a broad academic orientation and the right to award doctorates[5]. Including only this type of university ensures that our analysis focuses on institutions whose mission is teaching and research. We opted to exclude private HEIs due to the significant differences in legislation, institutional governance, and funding mechanisms compared to public institutions (Wolszczak-Derlacz; 2017). Additionally, we only include HEIs offering a limited number of distance learning programs (less than 20% of students enrolled in distance learning programs), recognizing that institutions primarily focused on distance learning can exhibit substantial variations in human resource management and facilities costs (Herberholz and Wigger; 2021). Finally, we also excluded very specialized institutions, such as music, arts, and military academies, and some institutions due to the presence of missing values. A de-

[5] In the European higher education system there are several institutions that focus on vocational training without having the right to award doctorates, such as the *Fachhochschule* in Austria or Germany.

tailed description of the sample selection procedure and the specific characteristics of HEs by country is presented in Appendix 3.A.

The final sample consists of panel dataset of 239 institutions in 10 European countries (Austria, Switzerland, Germany, Ireland, Lithuania, the Netherlands, Norway, Portugal, Sweden, and United Kingdom) observed from 2011 to 2019. Table 3.1 presents the descriptive statistics for the inputs and outputs of universities and their determinants.

Building on the extensive literature on university efficiency[6], we focus on teaching and research as the primary functions of universities. Our model includes two inputs and two outputs to capture these activities. The first input represents the total number of students enrolled in higher education programs (ISCED 5-7)[7] (x_1). As a second input we use the total number of academic staff, including professors, associate professors, and researchers (x_2). Personnel are quantified in Full-time equivalents (FTE), calculated as the actual working hours of HEI personnel during a reference period divided by the total hours typically worked by a full-time employee in the same period. This measure acount for the effective staff effort and reduces missing values compared to the same measure in headcounts. Therefore, we opt to use total academic personnel instead of disaggregating academic and technical staff numbers [8]. As output measure of research activity, we employ the total number publication (y_1), focusing on articles and reviews and excluding conference papers, book chapters, and data papers. The selection of an output indicator for university research activity is a highly debated issue in the literature on university efficiency. While various proxies are utilized, most studies select indicators based on publications or research grants. Research grants are often preferred due to their reflection of the market value of research, enabling consideration of both the quantity and quality of research (Johnes; 1997; Worthington; 2001). Conversely, bibliometric indicators, available in multidisciplinary databases, offer a less ambiguous measure of research output compared to grants, which are spent on research assistance and other facilities involved in the production process (Johnes and Johnes; 1993). However, Gralka et al. (2019), in comparing efficiency results obtained using research grants and several publication indicators, found a high correlation between estimated efficiency scores. Finally, to account for teaching activities, we use the total number of graduates (ISCED 5-7) ($y2$).

The parametric nature of the SF model requires assuming a functional form that represents the production technology. We employ the translog specification due to its

[6]For a comprehensive review of the literature on efficiency in higher education, see Witte and López-Torres (2017); Mergoni and De Witte (2022)

[7]International Standard Classification of Education (ISCED). ISCED 5 corresponds to Short-cycle tertiary education, ISCED 6 to Bachelor's or equivalent degrees, and ISCED 7 to Master's or equivalent degrees.

[8]We performed robustness checks on the human capital input. See Section 3.4.3

Table 3.1: Overall descriptive statistic for the variables distance function (years 2011-2019)

	Var.	Mean	s.d.	Min	Max
Inputs and outputs					
Total personnel (FTE)	x_1	2881	(2546)	195	15353
Enrolled students (ISCED 5-7)	x_2	17285	(9955)	1676	77825
Number of publications	y_1	1338	(1408)	5	8110
Graduates (ISCED 5-7)	y_2	4156	(2427)	275	13050
Determinants of inefficiency					
Average Share of tuition fees	$z_{0i,1}$	0.26	(0.29)	0	0.90
Average Share of third party funding	$z_{0i,2}$	0.20	(0.11)	0.01	0.79

Note: The number of observation are N = 296 institutions in 13 European countries.
Data source: ETER project. Download date Oct 2023 - SciVal. Download date Nov 2023

flexible nature[9]. Medical school expenses are notably higher across all departments due to elevated faculty salaries and increased costs associated with training and research (Agasisti and Salerno; 2007). To account for possible differences in technology, we include a hospital dummy, which equals one if the university has a medical school. Finally, we incorporate a linear time trend (t) to account for technological change. The translog output distance function model, with two inputs (x_1, x_2) and two outputs (y_1, y_2), can be expressed as:

$$\begin{aligned} -\log y_1 = {} & \beta_0 + \sum_{h=1}^{2} \beta_h \log\left(x_{h,it}\right) + \gamma \ \log\left(\frac{y_{2,it}}{y_{1,it}}\right) \\ & + \frac{1}{2}\left[\sum_{h=1}^{2}\sum_{k=1}^{2} \beta_{hk} \log\left(x_{h,it}\right)\log\left(x_{k,it}\right) + \gamma_2 \ \left[\log\left(\frac{y_{m,it}}{y_{1,it}}\right)\right]^2\right] \\ & + \sum_{h=1}^{2} \delta_{h2} \log\left(x_{h,it}\right) \log\left(\frac{y_{2,it}}{y_{1,it}}\right) + \lambda t + \tau H + u_{0i} + u_{it} + v_{0,i} + v_{it}. \end{aligned} \tag{3.9}$$

In order to examine the effects of different strategic choices that universities and policymakers may make in the long run, we include some determinants of persistent and transient inefficiency. As discussed above, financial resources for public supported HEIs mainly come from three main streams: core funding (from general government allocation), student fees, and third-party funding (from public and private organizations). Given that persistent (long-run) inefficiency does not change over time, the determinants of this term must also be time-invariant. We calculate the time average of the "*Share of tuition fees*" ($z_{0i,1}$) and the "*Share of third-party*" ($z_{0i,2}$) funding on total revenues to determine the impact of the funding strategy on long-term university performance.

[9] As a robustness check, we also employ a Cobb-Douglas functional form. The results are robust and detailed in Section 3.4.3.

Furthermore, we explore the effect of size by including a "*Large Universities*" dummy variable ($z_{0i,3}$), equal to one for institutes with more than 15000 students enrolled. Finally, we include a linear time trend (t) in the transient inefficiency to analyze the trend of short-term performance across the sample.

3.4 Empirical results

3.4.1 Technology and efficiency scores

Table 3.1 presents the estimates of three GTRE - SF specifications (M1, M2 to M3). Model M1 is a specification where no determinants of inefficiency are included, assuming that the four error terms are homoskedastic. In M2, we include country dummies in the frontier estimation, while the M3 specification is the most comprehensive as it incorporates determinants of persistent (long-run) and transient (short-term) inefficiency. In all specifications, we check for technological change by including linear time trends and test the presence of medical schools. The estimated technology parameters are shown in top panel of the Table 3.1 are all statistically significant and quite stable across specifications. The sign of the coefficient are coherent with theoretical expectation with the first order coefficient and significant across the three specifications.

The performance of the model is then assessed using the LR test[10] . M3 outperforms M1 and M2 as the critical value of the mixed χ^2 distribution with 4 degrees of freedom at the 1% significance level is equal to 17.75, which is smaller than the double difference of the likelihood values of M2 and M1. Further, the efficiency results are qualitatively consistent across the specifications. Therefore, subsequent analysis will be based on the outcomes derived from model M3.

Turning to the efficiency results, Table 3.2 presents the descriptive statistics of the estimated values, while Figure 3.1 shows the distribution of the overall efficiency. We observe that the average overall efficiency is 0.78, indicating a potential output expansion of 22%, with scores ranging from about 0.32 to 0.95. Moreover, the Figure 3.1 shows that the left tail of the distribution is rather long, indicating considerable heterogeneity in terms of efficiency within the European higher education sector. The results are consistent with other studies that compare universities at the European level, showing a wide disparity in efficiency among universities and countries (Wolszczak-Derlacz and Parteka; 2011; Wolszczak-Derlacz; 2017; Herberholz and Wigger; 2021).

[10]The LR statistic can be expressed as $LR = -2(ll_r - ll_u)$, where ll_r and ll_u represent the log-likelihood values of the restricted and unrestricted models respectively.

Table 3.1: University output distance function

Parameter	M1		M2		M3	
Production technology						
Intercept	-0.135***	(0.016)	0.204***	(0.035)	0.179***	(0.044)
log(x1)	-0.233***	(0.023)	-0.303***	(0.019)	-0.273***	(0.018)
log(x2)	-0.522***	(0.018)	-0.569***	(0.021)	-0.616***	(0.019)
log(y2/y1)	0.547***	(0.012)	0.608***	(0.015)	0.624***	(0.014)
0.5 * $log(x1)^2$	0.163***	(0.033)	0.128***	(0.032)	0.219***	(0.030)
0.5 * $log(x2)^2$	0.250***	(0.045)	0.259***	(0.047)	0.259***	(0.048)
0.5 * $log(y2/y1)^2$	0.097***	(0.005)	0.087***	(0.006)	0.092***	(0.006)
log(x1):log(x2)	-0.274***	(0.001)	-0.258***	(0.035)	-0.305***	(0.035)
log(x1):log(y2/y1)	0.046***	(0.041)	0.044***	(0.007)	0.079***	(0.007)
log(x2):log(y2/y1)	-0.138***	(0.034)	-0.126***	(0.013)	-0.139***	(0.013)
Hospital	-0.194***	(0.007)	-0.238***	(0.031)	-0.177***	(0.028)
t	-0.018***	(0.011)	-0.014***	(0.001)	-0.002**	(0.001)
1. Random noise component: $\log \sigma^2_{v_{it}}$						
(Intercept)	-6.129***	(0.114)	-6.019***	(0.111)	-5.578***	(0.050)
2. Transient (Short-run) inefficiency component: $\log \sigma^2_{u_{it}}$						
(Intercept)	-4.772***	(0.099)	-4.778***	(0.104)	-3.139***	(0.149)
t					-0.718***	(0.076)
3. Random effects component: $\log \sigma^2_{v_{0i}}$						
(Intercept)	-2.242***	(0.055)	-3.687***	(0.148)	-3.754***	(0.113)
4. Persistent (long-run) inefficiency component: $\log \sigma^2_{u_{0i}}$						
(Intercept)	-1.814***	(0.065)	-2.048***	(0.098)	-0.656***	(0.148)
Share Third Party					-5.608***	(0.605)
Share Tuition fees					-2.255***	(0.273)
Large universities					-1.079***	(0.206)
Country dummies	No		Yes		Yes	
N	239		239		239	
$\sum_{i=1}^{N} T_i$	2151		2151		2151	
Sim. logL	1945.03		2018.22		2101.25	

Note All input and output variables are natural logarithms and are normalized by their sample mean. Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

Table 3.2: Estimated transient, persistent and overall efficiency

	Mean	s.d.	Min	Max
Transient (Short-run) Efficiency	0.961	0.042	0.646	0.995
Persistent (Long-run) Efficiency	0.808	0.117	0.414	0.954
Overall Efficiency	0.777	0.118	0.329	0.948

However, unlike previous studies, we introduce the estimation of the persistent (long-run) efficiency term, which accounts for about 16% of the potential total output gains, given that the mean is 0.84[11]. Some universities exhibit notably low levels of persistent

[11] Note that, as shown in Equation (3.6), overall efficiency is the product of persistent and transient efficiency.

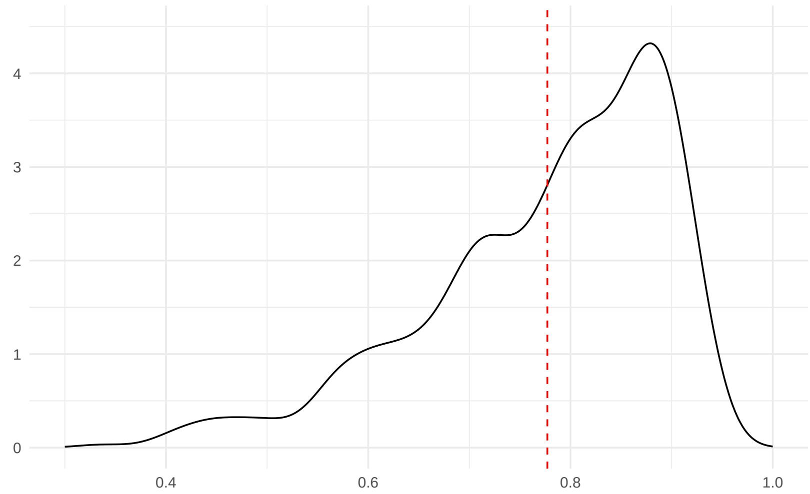

Figure 3.1: Kernel Density for Overall Efficiency. The dashed red vertical represents the efficiency mean value

inefficiency (with a minimum of 0.38), driving inefficiency towards the left tail of the distribution in Figure 3.1. Transient (short-term) efficiency shows a smaller dispersion among universities, with values ranging from 0.68 to 0.99. Further, the average efficiency is higher (about 0.96), suggesting only a marginal potential increase in output. Overall, universities tend to exhibit lower efficiency in the long run, while short-run efficiency is close to 100% for many institutions. These findings underline the importance of structural factors in understanding university performance.

3.4.2 Country differences and inefficiency determinants

Recognizing that factors such as the incentives imposed by national and regional authorities affect the response of national institutions in implementing strategy and managing their operations (Beath et al.; 2005; Agasisti and Berbegal-Mirabent; 2021), we explore efficiency results across countries. Figure 3.2 presents the kernel densities of overall efficiency by country and their respective means.

Differences between countries are relevant. For instance, countries like the Netherlands, the United Kingdom, and Ireland exhibit a high peak on the right side of the distribution. In contrast, others like Norway, Sweden, and Switzerland show peaks at lower efficiency levels. Additionally, countries like Germany and Lithuania display a long left tail, indicating considerable heterogeneity in efficiency within each country. Despite many universities achieving high efficiency, substantial performance disparities exist be-

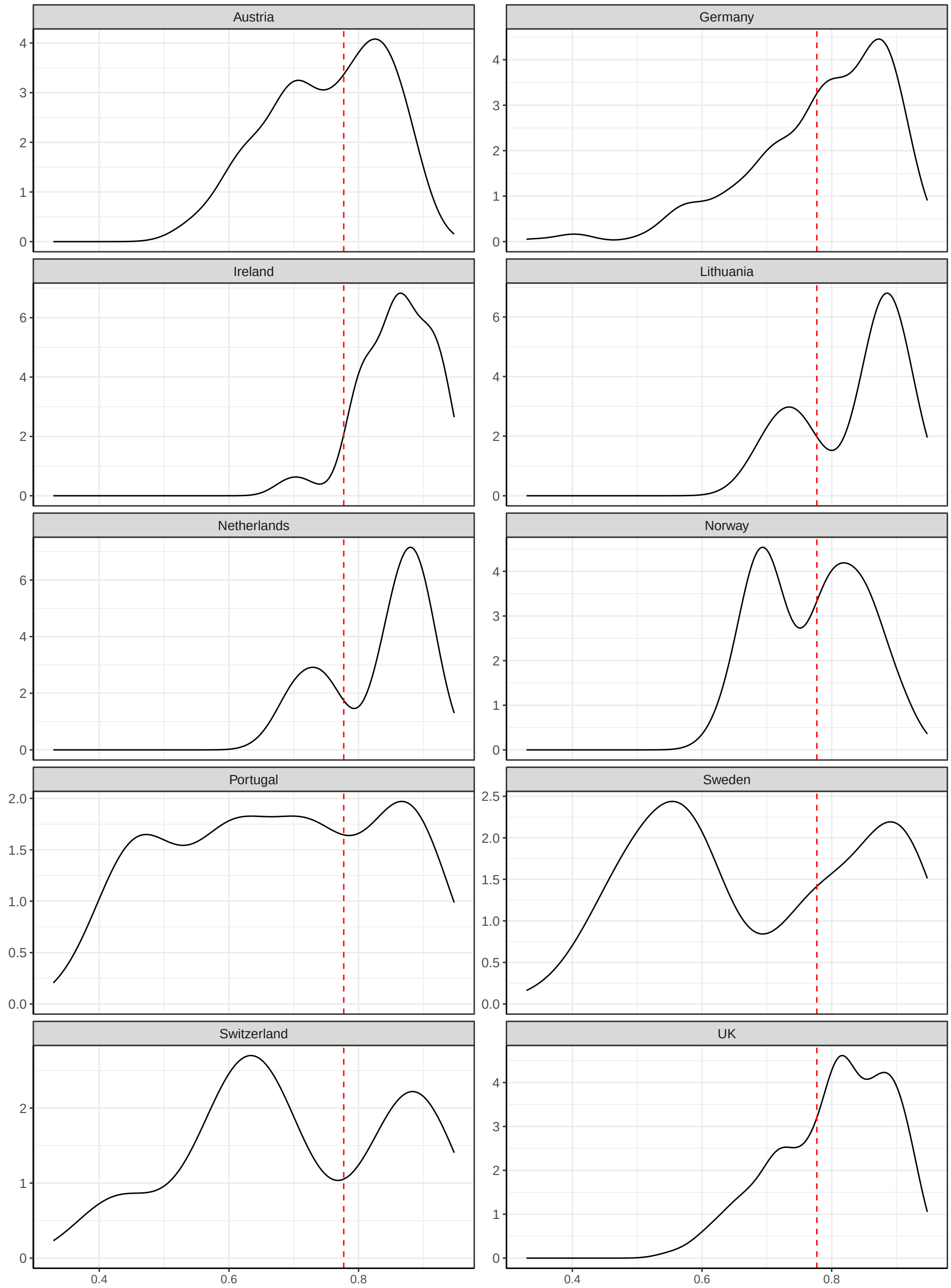

Figure 3.2: Kernel Density for Overall Efficiency by Country. The dashed red vertical line represents the mean efficiency of each country.

tween countries. Differences between countries are notable, with countries such as the Netherlands, the United Kingdom, and Ireland displaying a high peak on the right side of the distribution, while others like Norway, Sweden, and Switzerland show peaks at lower efficiency levels. Furthermore, countries like Germany and Lithuania exhibit a long left tail, indicating considerable heterogeneity in efficiency within each country. These results suggest that, while most universities achieve high efficiency results, there are significant performance gaps between countries. Disentangling long-run and short-term efficiency reveals much about the nature of efficiency gaps. Figure 3.3 and Figure 3.4 illustrate the box plots of persistent and transient inefficiency by country. For ease of comparison, the range on the vertical axis is consistent across all countries. Analysis of the figures indicates that the gap between countries is primarily driven by the persistent term, reflecting differences that emerged in Figure 3.2. These results confirm that long-term factors significantly contribute to efficiency gaps. The influence of policies adopted by respective countries on university efficiency, as highlighted by these disparities at the national level, is likely to persist over time, resulting in long-term efficiency disparities between countries due to different target schemes and incentives.

To better understand the nature of these long-term factors, we examine the determinants of inefficiency conditions, assuming that the level of competitive funding and the design of funding mechanisms affect university performance in the long run. The bottom panel of Table 3.1 shows the estimated parameters of each error term, the persistent and transient efficiency terms, and their determinants. The direction of the coefficients reveals the relationship between the variable and the inefficiency term: a parameter with a positive sign in the inefficiency components implies an increase in inefficiency, consequently reducing university performance. As described in Section 3.3, we explore the effect of the composition of the revenue on long-run inefficiency. The coefficients of the inefficiency determinants on persistent inefficiency are estimated via Equation (3.7), in which $\sigma_{u_{0i}}$ is a function of the average levels of the share of tuition fees and third-party funding. Furthermore, to control for size effects, we include a Large Universities dummy variable, equal to one whether the institutes have more than 1500 students enrolled. In estimating short-term inefficiency, we include a time trend to test for any average change in efficiency (Equation (3.8)). The coefficient associated with the time trend t in the bottom panel of Table 3.1 -Transient (Short-run) Inefficiency Component - indicates that transient efficiency is increasing across the sample. Consistent with the findings on the higher education systems of individual countries (Agasisti et al.; 2016; Gralka; 2018; Martínez-Campillo and Fernández-Santos; 2020), these results suggest that European universities have been on a positive trend of increasing efficiency over the last decade.

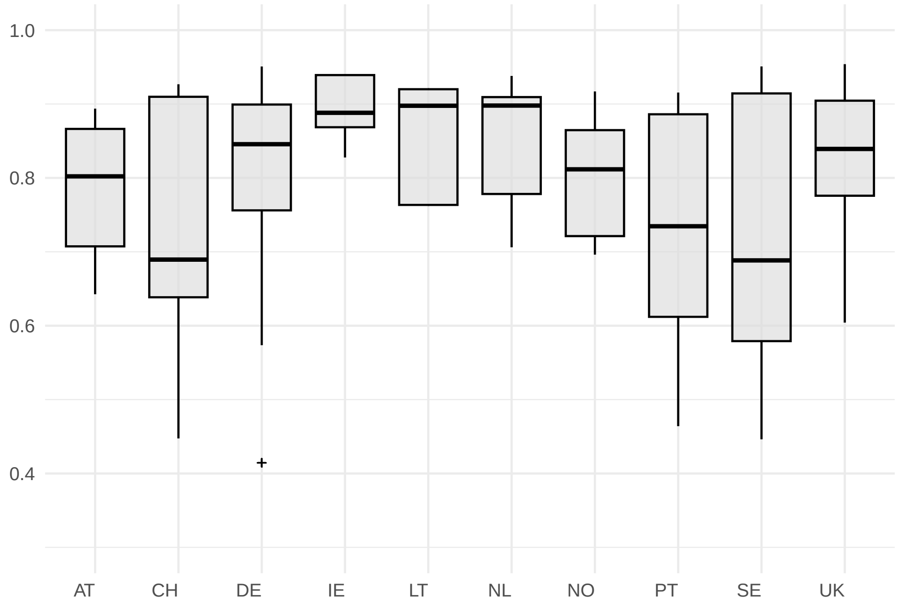

Figure 3.3: Box Plot of the Persistent (Long-run) Efficiency by Country.

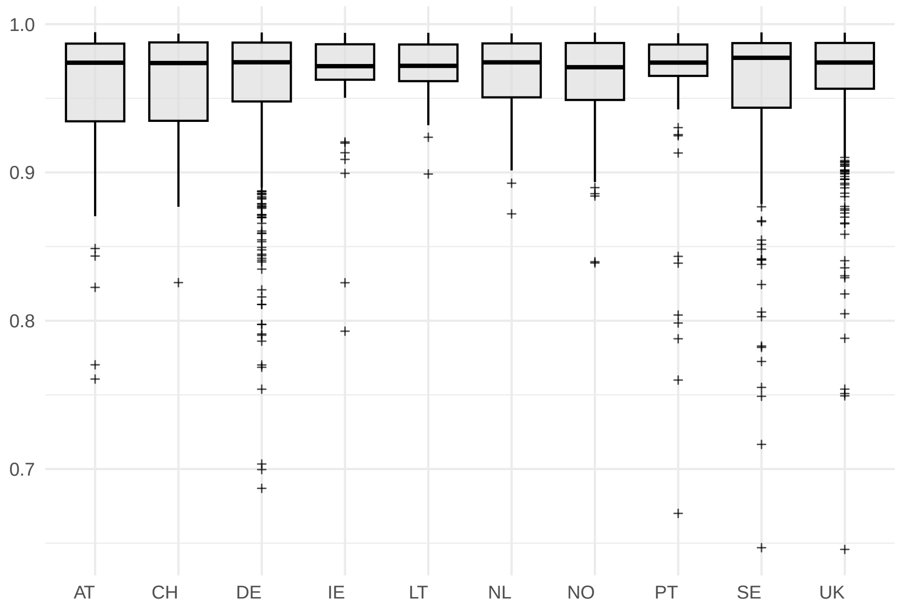

Figure 3.4: Box Plot of the Transient (Short-run) Efficiency by Country.

Turning our attention to the factors that make universities persistently efficient in the long run, we focus on the estimation parameter of $\ln \sigma^2_{u_{u0i}}$ in the bottom panel of Table 3.1 - Persistent (long-run) inefficiency component. The results reveal that the composition of revenues is a relevant factor in explaining long-run inefficiency, as both the average share of tuition fees and the share of third-party funding are statistically significant. The negative sign of the estimated parameter suggests that universities with a higher share of revenues from tuition fees and third-party tend to be more efficient in their long run operations. This view is coherent with the idea that a competition effects exist both in terms of fees and projects funding Agasisti (2009); Cherchye and Abeele (2005); Bolli et al. (2016). Further, in line with the literature (Bonaccorsi et al.; 2007; Daraio et al.; 2015), the Large university dummy also returns a negative sign, suggesting that larger universities in terms of enrolled students are associated with higher persistent efficiency.

3.4.3 Robustness analysis

We conduct several robustness checks to thoroughly examine the robustness of our findings across different model specifications. In Table 3.3, we present the results of these checks. Initially, we examine the choice of the functional form by employing a Cobb-Douglas specification (M4). While the coefficients exhibit expected signs, consistent with our translog specification, we notice a slight deviation in the coefficient associated with the share of third-party support, which appears smaller. Despite this discrepancy, the likelihood ratio test favors the model (M3), as outlined in Section 3.4.1. Moving forward, we delve deeper into the choice of human capital input in our following robustness checks (M5 and M6). In M5, we recalibrate the model using the total number of academic staff in place of the total number of personnel. Therefore, in the second column of Table **??**, x_2 now represents the academic staff. In M6, we subsequently segmented the total personnel into academic staff (represented as x_1) and technical staff (x_3), alongside the number of students (x_2). This change resulted in a reduction of universities in our sample due to incomplete data on technical staff. Despite these changes in the model specifications, the coefficients are generally in line with theoretical expectations. However, the first-order coefficient associated with technical staff lacks statistical significance. In addition, the coefficient for large universities is not statistically significant, with a particularly high coefficient suggesting potential inconsistency in the estimates. Again, according to the log-likelihood test, the model specification (M3) remains the most appropriate.

Table 3.3: Robustness: University output distance function

Parameter	M4		M5		M6	
Production technology						
(Intercept)	0.211***	(0.043)	0.155***	(0.039)	0.205***	(0.036)
log(x1)	-0.256***	(0.016)	-0.125***	(0.017)	-0.0.156	(0.019)
log(x2)	-0.622***	(0.017)	-0.634***	(0.021)	-0.656***	(0.023)
log(x3)					-0.018***	(0.023)
log(y2/y1)	0.764***	(0.009)	0.615***	(0.016)	0.650***	(0.015)
Hospital	-0.179***	(0.025)	-0.350***	(0.038)	-0.187***	(0.029)
t	0.001	(0.001)	-0.007***	(0.001)	-0.006***	(0.001)
0.5 * $log(x1)^2$			0.186***	(0.054)	-0.050	(0.035)
0.5 * $log(x2)^2$			0.278***	(0.038)	0.279***	(0.054)
0.5 * $log(x3)^2$					-0.108	(0.094)
0.5 * $log(y2/y1)^2$			0.074***	(0.006)	0.069***	(0.006)
log(x1):log(x2)			-0.296***	(0.039)	0.241***	(0.037)
log(x1):log(y2/y1)			0.049***	(0.008)	0.069***	(0.014)
log(x2):log(y2/y1)			-0.122***	(0.013)	-0.148***	(0.015)
log(x3):log(y2/y1)					-0.0032	(0.0172)
log(x1):log(x3)					-0.279***	(0.053)
log(x2):log(x3)					-0.159**	(0.053)
1. Random noise component: $\log \sigma^2_{v_{it}}$						
(Intercept)	-5.477***	(0.053)	-5.514***	(0.050)	-5.549***	(0.051)
2. Transient (Short-run) inefficiency component: $\log \sigma^2_{u_{it}}$						
(Intercept)	-3.043***	(0.147)	-3.303***	(0.159)	-3.257***	(0.155)
t	-0.662***	(0.069)	-0.687***	(0.079)	0.667***	(0.075)
3. Random effects component: $\log \sigma^2_{v_{0i}}$						
(Intercept)	-4.256***	(0.168)	-3.541***	(0.126)	-3.241***	(0.114)
4. Persistent (long-run) inefficiency component: $\log \sigma^2_{u_{0i}}$						
(Intercept)	-1.373***	(0.143)	-0.827***	(0.124)	-1.397***	(0.255)
Share Third Party	-0.333***	(0.463)	-2.390***	(0.432)	-5.570***	(1013)
Share Tuition fees	-2.428***	(0.290)	-2.319***	(0.276)	-2.035***	(0.427)
Large universities	-0.038***	(0.059)	-0.864***	(0.178)	33.52	(2.5e+0)
Country dummies	Yes		Yes		Yes	
N	239		239		221	
$\sum_{i=1}^{N} T_i$	2151		2151		2133	
Sim. logL	1965.32		2008.78		2051.94	

Note All input and output variables are natural logarithms and are normalized by their sample mean. Standard errors in parentheses; $^{*}p < .10$, $^{**}p < .05$ *** $p < .01$.

3.5 Discussion and conclusions

This paper analyses the efficiency of 239 European higher education institutions in 10 countries (Austria, Switzerland, Germany, Ireland, Lithuania, the Netherlands, Norway, Portugal, Sweden, and the UK) between 2011 and 2019. Using a GTRE stochastic frontier model, we decompose overall efficiency into persistent (Long-run) and transient (Short-term) components.

The results reveal that the efficiency in the European HE sector is relatively high, albeit there are significant differences in efficiency scores between institutions and countries. Further, universities tend to exhibit lower efficiency in the long run, contrasting with near-optimal short-term efficiency observed in many institutions.

Delving into the determinants of inefficiency yields valuable insights for university administrators and policymakers seeking to enhance the efficiency of higher education institutions. The composition of revenues emerges as a important factor in explaining long-term inefficiency. In particular, a high share of tuition fees and third-party funding in total income correlates with better performance. Moreover, differences between higher education systems appear to be driven primarily by long-term efficiency outcomes, underlining the importance of structural factors in explaining performance levels within the sector.

Overall, these findings highlight the central role of national authorities and governments in shaping both the normative environment and financial incentives. Their involvement in facilitating different forms of cost-sharing and in designing effective performance-based allocation mechanisms is central to optimizing university performance.

It's important to acknowledge certain limitations of the paper. In particular, the factors considered are primarily assessed using quantitative measures. However, the quality measure in efficiency analysis represents a well-known limitation that, although challenging, needs to be addressed. Additionally, it's important to note that several outputs of HEIs are not measurable. For example, quantifying the impact of a university's third mission poses significant challenges. In addition, the lack of available data on the mechanisms for allocating government funds is a notable limitation to the study. However, this limitation also opens up new research opportunities and points to future avenues of investigation. Exploring how specific national incentives correlate with efficiency levels could provide valuable insights for identifying potential policy directions.

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3.A Appendix A: Sample selection and composition

The ETER database is a valuable tool for cross-country analysis of higher education systems, providing detailed microdata on institutional activities and adhering to rigorous data validation and control procedures to improve comparability across institutions. However, given the considerable heterogeneity among Higher Education Institutions, a further conceptual effort is required when conducting a cross-country analysis. This diversity includes institutional mandate, mission, activity mix, legal status, and institutional governance. When conducting cross-country analysis, it is crucial to focus on reducing heterogeneity by clearly defining the primary research goals and establishing precise criteria for sample selection to improve inter-institutional comparability.

We have identified three main criteria to select comparable institutions. Specifically, we restrict the usage to four intensification variables in the ETER dataset: 1) Institution category: We select institutions categorized as "UNI" (1) to ensure comparability; 2) Legal status: We include institutions categorized as either public (0) or private government-dependent (2) to maintain consistency; 3); PhD status: We choose institutions with a PhD status of 1 to ensure they have the legal right to award PhD degrees; Distance education institution: We select institutions where less than 20% of students are enrolled in distance programs (0), avoiding institutions with a substantial share or majority of students in distance education.

Finally, we drop HEIs with missing values and exclude X observations. We also exclude extreme outliers by applying a number of filters to the sample, including performing Grubbs' test. This process excludes only 16 HEIs. Table A1 shows the composition of the final sample.

Table A1: Sample composition and HEIs characteristics

Country	Number of HEIs	Hospital	Large Universities
Austria	11	0	1
Switzerland	8	3	3
Germany	66	10	42
Ireland	5	0	1
Lithuania	3	1	0
Netherlands	13	0	11
Norway	8	1	4
Portugal	9	0	0
Sweden	24	2	7
United Kingdom	92	21	20
Total	239	38	89

Table A2: List of HEIs in the sample

Lp.	Country	Code	University
1	Austria	AT	Graz University of Technology
2	Austria	AT	Johannes Kepler University Linz
3	Austria	AT	University of Graz
4	Austria	AT	University of Innsbruck
5	Austria	AT	University of Klagenfurt
6	Austria	AT	University of Leoben
7	Austria	AT	University of Natural Resources and Life Sciences
8	Austria	AT	University of Salzburg
9	Austria	AT	University of Vienna
10	Austria	AT	Vienna University of Economics and Business
11	Austria	AT	Vienna University of Technology
12	Switzerland	CH	University of Bern
13	Switzerland	CH	University of Fribourg
14	Switzerland	CH	University of Geneva
15	Switzerland	CH	University of Lausanne
16	Switzerland	CH	University of Lucerne
17	Switzerland	CH	University of Neuchatel
18	Switzerland	CH	University of St. Gallen
19	Switzerland	CH	Università della Svizzera italiana
20	Germany	DE	Augsburg University
21	Germany	DE	Bauhaus-Universität Weimar
22	Germany	DE	Bielefeld University
23	Germany	DE	Clausthal University of Technology
24	Germany	DE	Europe University Viadrina
25	Germany	DE	Free University of Berlin
26	Germany	DE	Friedrich Schiller University Jena
27	Germany	DE	Friedrich-Alexander University Erlangen-Nürnberg
28	Germany	DE	Goethe University Frankfurt
29	Germany	DE	HafenCity University Hamburg
30	Germany	DE	Hamburg University of Technology
31	Germany	DE	Heidelberg University
32	Germany	DE	Heinrich Heine University Düsseldorf
33	Germany	DE	Humboldt University of Berlin
34	Germany	DE	Ilmenau University of Technology
35	Germany	DE	Johannes Gutenberg University Mainz
36	Germany	DE	Justus Liebig University Giessen
37	Germany	DE	Karlsruhe Institute of Technology
38	Germany	DE	Kiel University
39	Germany	DE	Leibniz University Hannover
40	Germany	DE	Leipzig University
41	Germany	DE	Leuphana University of Lüneburg

Table A2: (continued from previous page)

Lp.	Country	Code	University
42	Germany	DE	Ludwig Maximilian University of Munich
43	Germany	DE	Martin Luther University Halle-Wittenberg
44	Germany	DE	Osnabrück University
45	Germany	DE	Paderborn University
46	Germany	DE	Ruhr University Bochum
47	Germany	DE	Saarland University
48	Germany	DE	TU Dortmund University
49	Germany	DE	Technical University of Berlin
50	Germany	DE	Technical University of Braunschweig
51	Germany	DE	Technische Universität Darmstadt
52	Germany	DE	Technische Universität Dresden
53	Germany	DE	Trier University
54	Germany	DE	Ulm University
55	Germany	DE	University of Bamberg
56	Germany	DE	University of Bayreuth
57	Germany	DE	University of Bonn
58	Germany	DE	University of Bremen
59	Germany	DE	University of Cologne
60	Germany	DE	University of Duisburg-Essen
61	Germany	DE	University of Erfurt
62	Germany	DE	University of Flensburg
63	Germany	DE	University of Freiburg
64	Germany	DE	University of Greifswald
65	Germany	DE	University of Göttingen
66	Germany	DE	University of Hamburg
67	Germany	DE	University of Hildesheim
68	Germany	DE	University of Hohenheim
69	Germany	DE	University of Kassel
70	Germany	DE	University of Koblenz-Landau
71	Germany	DE	University of Konstanz
72	Germany	DE	University of Mannheim
73	Germany	DE	University of Marburg
74	Germany	DE	University of Münster
75	Germany	DE	University of Oldenburg
76	Germany	DE	University of Passau
77	Germany	DE	University of Potsdam
78	Germany	DE	University of Regensburg
79	Germany	DE	University of Rostock
80	Germany	DE	University of Siegen
81	Germany	DE	University of Stuttgart
82	Germany	DE	University of Tübingen

Table A2: (continued from previous page)

Lp.	Country	Code	University
83	Germany	DE	University of Vechta
84	Germany	DE	University of Wuppertal
85	Germany	DE	University of Würzburg
86	Ireland	IE	Maynooth University
87	Ireland	IE	Trinity College Dublin
88	Ireland	IE	University College Dublin
89	Ireland	IE	University of Galway
90	Ireland	IE	University of Limerick
91	Lithuania	LT	Kaunas University of Technology
92	Lithuania	LT	Lithuanian University of Health Sciences
93	Lithuania	LT	Vilnius Gediminas Technical University
94	Netherlands	NL	Delft University of Technology
95	Netherlands	NL	Eindhoven University of Technology
96	Netherlands	NL	Erasmus University Rotterdam
97	Netherlands	NL	Leiden University
98	Netherlands	NL	Maastricht University
99	Netherlands	NL	Radboud University Nijmegen
100	Netherlands	NL	Tilburg University
101	Netherlands	NL	University of Amsterdam
102	Netherlands	NL	University of Groningen
103	Netherlands	NL	University of Twente
104	Netherlands	NL	Utrecht University
105	Netherlands	NL	Vrije Universiteit Amsterdam
106	Netherlands	NL	Wageningen University & Research
107	Norway	NO	Nord University
108	Norway	NO	Norwegian University of Life Sciences
109	Norway	NO	Norwegian University of Science and Technology
110	Norway	NO	University of Agder
111	Norway	NO	University of Bergen
112	Norway	NO	University of Oslo
113	Norway	NO	University of Stavanger
114	Norway	NO	University of Tromsø – The Arctic University of Norway
115	Portugal	PT	NOVA University Lisbon
116	Portugal	PT	Universidade de Trás-os-Montes e Alto Douro
117	Portugal	PT	University of Algarve
118	Portugal	PT	University of Beira Interior
119	Portugal	PT	University of Coimbra
120	Portugal	PT	University of Madeira
121	Portugal	PT	University of Minho
122	Portugal	PT	University of the Azores
123	Portugal	PT	University of Évora

Table A2: (continued from previous page)

Lp.	Country	Code	University
124	Sweden	SE	Blekinge Institute of Technology
125	Sweden	SE	Chalmers University of Technology
126	Sweden	SE	Dalarna University
127	Sweden	SE	Halmstad University
128	Sweden	SE	Jönköping University
129	Sweden	SE	KTH Royal Institute of Technology
130	Sweden	SE	Karlstad University
131	Sweden	SE	Linköping University
132	Sweden	SE	Linnaeus University
133	Sweden	SE	Luleå University of Technology
134	Sweden	SE	Lund University
135	Sweden	SE	Malmö University
136	Sweden	SE	Mid Sweden University
137	Sweden	SE	Mälardalen University
138	Sweden	SE	Stockholm School of Economics
139	Sweden	SE	Stockholm University
140	Sweden	SE	Södertörn University
141	Sweden	SE	Umeå University
142	Sweden	SE	University of Borås
143	Sweden	SE	University of Gothenburg
144	Sweden	SE	University of Gävle
145	Sweden	SE	University of Skövde
146	Sweden	SE	Uppsala University
147	Sweden	SE	Örebro University
148	United Kingdom	UK	Aberystwyth University
149	United Kingdom	UK	Anglia Ruskin University
150	United Kingdom	UK	Aston University
151	United Kingdom	UK	Bangor University
152	United Kingdom	UK	Bath Spa University
153	United Kingdom	UK	Birkbeck University of London
154	United Kingdom	UK	Bournemouth University
155	United Kingdom	UK	Brunel University London
156	United Kingdom	UK	Canterbury Christ Church University
157	United Kingdom	UK	Cardiff Metropolitan University
158	United Kingdom	UK	Cardiff University
159	United Kingdom	UK	City, University of London
160	United Kingdom	UK	Coventry University
161	United Kingdom	UK	De Montfort University
162	United Kingdom	UK	Durham University
163	United Kingdom	UK	Edge Hill University
164	United Kingdom	UK	Edinburgh Napier University

Table A2: (continued from previous page)

Lp.	Country	Code	University
165	United Kingdom	UK	Glasgow Caledonian University
166	United Kingdom	UK	Goldsmiths, University of London
167	United Kingdom	UK	Heriot-Watt University
168	United Kingdom	UK	Keele University
169	United Kingdom	UK	Kingston University
170	United Kingdom	UK	Lancaster University
171	United Kingdom	UK	Leeds Beckett University
172	United Kingdom	UK	Liverpool John Moores University
173	United Kingdom	UK	London Metropolitan University
174	United Kingdom	UK	Loughborough University
175	United Kingdom	UK	Manchester Metropolitan University
176	United Kingdom	UK	Middlesex University
177	United Kingdom	UK	Newcastle University
178	United Kingdom	UK	Northumbria University
179	United Kingdom	UK	Oxford Brookes University
180	United Kingdom	UK	Queen Margaret University
181	United Kingdom	UK	Queen Mary University of London
182	United Kingdom	UK	Queen's University Belfast
183	United Kingdom	UK	Robert Gordon University
184	United Kingdom	UK	Roehampton University
185	United Kingdom	UK	Royal Holloway University of London
186	United Kingdom	UK	Royal Veterinary College University of London
187	United Kingdom	UK	SOAS University of London
188	United Kingdom	UK	Sheffield Hallam University
189	United Kingdom	UK	Solent University
190	United Kingdom	UK	Staffordshire University
191	United Kingdom	UK	Swansea University
192	United Kingdom	UK	Teesside University
193	United Kingdom	UK	The London School of Economics and Political Science
194	United Kingdom	UK	University of Aberdeen
195	United Kingdom	UK	University of Bath
196	United Kingdom	UK	University of Bedfordshire
197	United Kingdom	UK	University of Bradford
198	United Kingdom	UK	University of Brighton
199	United Kingdom	UK	University of Bristol
200	United Kingdom	UK	University of Central Lancashire
201	United Kingdom	UK	University of Chester
202	United Kingdom	UK	University of Cumbria
203	United Kingdom	UK	University of Derby
204	United Kingdom	UK	University of Dundee
205	United Kingdom	UK	University of East Anglia

Table A2: (continued from previous page)

Lp.	Country	Code	University
206	United Kingdom	UK	University of East London
207	United Kingdom	UK	University of Essex
208	United Kingdom	UK	University of Exeter
209	United Kingdom	UK	University of Glasgow
210	United Kingdom	UK	University of Greenwich
211	United Kingdom	UK	University of Hertfordshire
212	United Kingdom	UK	University of Hull
213	United Kingdom	UK	University of Kent
214	United Kingdom	UK	University of Leicester
215	United Kingdom	UK	University of Lincoln
216	United Kingdom	UK	University of Liverpool
217	United Kingdom	UK	University of Northampton
218	United Kingdom	UK	University of Plymouth
219	United Kingdom	UK	University of Portsmouth
220	United Kingdom	UK	University of Reading
221	United Kingdom	UK	University of Salford
222	United Kingdom	UK	University of Sheffield
223	United Kingdom	UK	University of Southampton
224	United Kingdom	UK	University of St Andrews
225	United Kingdom	UK	University of Stirling
226	United Kingdom	UK	University of Strathclyde
227	United Kingdom	UK	University of Sunderland
228	United Kingdom	UK	University of Surrey
229	United Kingdom	UK	University of Sussex
230	United Kingdom	UK	University of Wales Trinity Saint David
231	United Kingdom	UK	University of Warwick
232	United Kingdom	UK	University of Westminster
233	United Kingdom	UK	University of Winchester
234	United Kingdom	UK	University of Wolverhampton
235	United Kingdom	UK	University of Worcester
236	United Kingdom	UK	University of the West of England
237	United Kingdom	UK	University of the West of Scotland
238	United Kingdom	UK	Wrexham Glyndwr University
239	United Kingdom	UK	York St John University